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Part I: Single-Intersection Policies

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16. Abstract

Common logic as well as analytical studies indicate that demand-responsive traffic control can very significantly improve urban street network performance. Yet effective traffic-responsive control has eluded transportation system researchers for many years--the main stumbling blocks being the inadequacy of predicted data from past traffic behavior and the unmet requirements for real-time optimal control techniques. This study develops innovative approaches to the urban traffic control problem using on-line traffic models which relax the reliance on predicted data, and decentralized optimization strategies which are amenable to real-time execution. The new methodologies are particularly suited for implementation via existing microprocessor technologies.

This report presents the studies undertaken and results achieved in Phase I of the research. It describes in detail the development and testing of models and strategies for real-time computation of optimal control policies for single intersections. These strategies lay a foundation for the establishment of demand-responsive decentralized urban traffic control on a systemwide basis.

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METRIC CONVERSION FACTORS

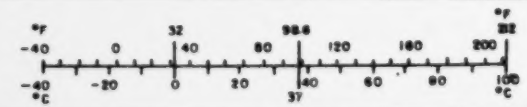
Approximate Conversions to Metric Measures

Symbol	When You Know	Multiply by	To Find	Symbol
	LENGTH			
in	inches	*2.5	centimeters	cm
ft	feet	30	centimeters	cm
yd	yards	0.9	meters	m
mi	miles	1.6	kilometers	km
	AREA			
in^2	square inches	6.5	square centimeters	cm^2
ft^2	square feet	0.09	square meters	m^2
yd^2	square yards	0.8	square meters	m^2
mi^2	square miles	2.6	square kilometers	km^2
	acres	0.4	hectares	ha
	MASS (weight)			
oz	ounces	28	grams	g
lb	pounds	0.45	kilograms	kg
	short tons (2000 lb)	0.9	tonnes	t
	VOLUME			
tsp	teaspoons	5	milliliters	ml
Tbsp	tablespoons	15	milliliters	ml
fl oz	fluid ounces	30	milliliters	ml
c	cups	0.24	liters	l
pt	pints	0.47	liters	l
qt	quarts	0.95	liters	l
gal	gallons	3.8	liters	l
ft^3	cubic feet	0.03	cubic meters	m^3
yd^3	cubic yards	0.76	cubic meters	m^3
	TEMPERATURE (exact)			
°F	Fahrenheit temperature	5/9 (after subtracting 32)	Celsius temperature	°C

*1 in = 2.54 (exactly). For other exact conversions and more detailed tables, see NBS Misc. Publ. 286, Units of Weights and Measures, Price $2.25, SD Catalog No. C13.10:286.

Approximate Conversions from Metric Measures

Symbol	When You Know	Multiply by	To Find	Symbol
	LENGTH			
mm	millimeters	0.04	inches	in
cm	centimeters	0.4	inches	in
m	meters	3.3	feet	ft
m	meters	1.1	yards	yd
km	kilometers	0.6	miles	mi
	AREA			
cm^2	square centimeters	0.16	square inches	in^2
m^2	square meters	1.2	square yards	yd^2
km^2	square kilometers	0.4	square miles	mi^2
ha	hectares (10,000 m^2)	2.5	acres	
	MASS (weight)			
g	grams	0.035	ounces	oz
kg	kilograms	2.2	pounds	lb
t	tonnes (1000 kg)	1.1	short tons	
	VOLUME			
ml	milliliters	0.03	fluid ounces	fl oz
l	liters	2.1	pints	pt
l	liters	1.06	quarts	qt
l	liters	0.26	gallons	gal
m^3	cubic meters	35	cubic feet	ft^3
m^3	cubic meters	1.3	cubic yards	yd^3
	TEMPERATURE (exact)			
°C	Celsius temperature	9/5 (then add 32)	Fahrenheit temperature	°F



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EXECUTIVE SUMMARY

a. Introduction

Effective traffic control in urban road networks is a major contributing element to the performance of the urban transportation system. The development of traffic control methods followed closely the development of computerized hardware and software control technologies. Logical considerations, as well as results of various analytical studies, indicate that demand-responsive traffic control can very significantly improve urban street network performance. Yet, despite a number of attempts to develop such strategies, traffic responsive control on a systemwide basis has eluded transportation system researchers for many years. A close examination of these experiments reveals that it is not the logical premises that have failed, but the models and techniques that were implemented could not produce the desired results. The main stumbling blocks have been identified to be: (a) the lack of adequate on-line traffic flow information; and, (b) the unmet requirements for computational methods that can produce optimal controls in real-time.

b. Problem Studied

The dramatic advances in microprocessor technologies during the past few years have opened up new horizons and opportunities for demand-responsive control that were not imaginable in the past. Naturally, the newly developed hardware technologies require the development of entirely new control concepts. Following a review of existing control strategies and past experimentations with traffic-responsive strategies, the following requirements for demand-responsive control strategies were formulated:

- The strategies shall provide better performance than off-line methods. This is obviously the primary criterion, but it has not always been recognized explicitly in previous efforts.
- There is a need for the development of new concepts and not merely the extrapolation of existing concepts. As demonstrated by the experiments reviewed in this report, effective responsiveness can not be achieved by just implementing off-line methods at an increased frequency. New methods altogether must be developed.
- They must be truly demand-responsive, i.e., adapt to actual traffic conditions and not to historical or predicted values that may be far off from the actual ones.
- They should not be arbitrarily restricted to control periods of any particular length, but should be amenable to updating at any time, at any location.

- They should not be encumbered by a rigid network model structure that requires extensive centralized computer capability. Instead, they should be based on decentralized decision-making that requires the use of only those traffic data that are directly pertinent to the decisions that have to be made at a particular location.

- They should obviate the conventional notions of offset, split, and cycle time, which are inherent in all existing signal optimization methods and inhibit their adaptability. The pattern of signal controls at any intersection should consist of a continuously varying, demand-responsive, sequence of ON (effective green) and OFF (effective red) times that are only subjected to appropriate lower and upper bounds.

This report describes the studies undertaken toward accomplishing these goals and the results achieved so far.

c. Results Achieved

Three different computer programs have been developed; they are all acronymed OPAC-Optimization Policies for Adaptive Control.

OPAC-1: A Dynamic-Programming-based program that calculates globally optimal demand-responsive traffic control policies. These policies serve as a standard for assessing the performance of all other strategies.

OPAC-2: A simplified search procedure for calculating optimal traffic control policies. This program serves as a basic building-block for demand-responsive control since it is amenable to on-line implementation.

R-OPAC: A rolling horizon strategy (therefore, R-OPAC) that computes demand-responsive control policies using an on-line traffic model which is continuously updated by readily available traffic flow information. The computer processing time is much reduced (compared to OPAC-1) and the strategy can be implemented in real-time using existing microprocessor technology. ROPAC is thus a very promising candidate strategy for demand-responsive decentralized control on a systemwide basis.

The computational tests conducted in this study show that ROPAC can achieve, under ideal conditions, very substantial savings in delay (up to 60%, see Figure 5.7) when compared to conventional fixed-time settings. Although it is not expected that the same results could be replicated in practice, these tests indicate very significant potential opportunities for improving traffic performance through demand-responsive control.

d. Utilization of Results

Modern traffic control systems are being continuously installed and existing systems upgraded and replaced. There are an estimated 250,000 signal-controlled intersections in the United States, and various Federal programs provide extensive assistance to states for improving their performance. Because they require relatively low capital investments, the cost-effectiveness of such improvements exceeds by far that of other, more capital-intensive, measures. With the advent of new hardware and software technologies, the benefits from the deployment of these tehcnologies can be rapidly realized by both operators and users of the transportation system.

e. Conclusion

The results of the studies undertaken so far indicate that real-time optimal traffic control, that overcomes the handicaps of previous attempts, is feasible and can provide very significant benefits in traffic performance measures (travel time, energy comsumption, pollutant emissions, etc.) over existing strategies. In fact, realization of these potential benefits would constitute a major breakthrough in urban traffic control methodology. However, several additional research and development steps are still required before implementation can be contemplated.

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1. INTRODUCTION

Mobility in urban areas depends very much on the effective utilization of the street and freeway system. It has long been recognized that the intersections of urban arterial streets, where large volumes of conflicting vehicular traffic streams are processed, are the critical elements in any urban street system. The safe and efficient movement of traffic through these conflict points is almost totally a function of traffic signalling equipment and traffic control techniques.

The development of traffic control signal systems for urban streets has paralleled the development and use of the automobile. It is characterized by a wide variety of control technology and equipment. Many advances have occurred in the last decade which has seen the introduction of computer-based traffic control systems in ever-increasing numbers. Several hundred such systems have already been installed or are under development throughout the world.

A large variety of procedures for computing signal timings have evolved over the years. Initially the methods were manual, such as the time-space diagram. Calculations were later computerized using sophisticated network optimization techniques. The results of the calculations may be transferred to a digital computer that directly controls the traffic lights (on-line), or that computes signal timing plans which are subsequently applied to control traffic lights (off-line). Both techniques are known as control strategies.

The modern digital computer was applied to traffic control in the 1960's. The first application took place in Toronto, Canada. Shortly thereafter, systems were installed in Glasgow, Scotland, and in the United States in San Jose and Wichita Falls. These systems used general-purpose process control computers, the forerunners

of today's minicomputers. With the exception of the experiments performed by the British in Glasgow during the late 1960's, the signals were controlled by using stored timing plans that were calculated using off-line optimization techniques.

In the 1970's there has been a continuing development of both the hardware and software strategies used in digital computer controlled signal systems. The computer hardware has become smaller, faster, and less costly, and the calculation procedures have become more sophisticated. At the same time intensive efforts have been made to develop strategies that are more traffic responsive. For a variety of reasons these strategies have not, generally, been as successful as the fixed-time strategies. A review of the major experiments in strategy development and testing, and the lessons derived from those experiments, as far as traffic-responsiveness is concerned, is given in Chapter 2. A major reason for the relative ineffectiveness of traffic-responsive control to date appears to be that analysts have attempted to adapt existing off-line methods to on-line operation rather than developing new concepts and methods.

With the emergence of the microprocessor technologies, new horizons and opportunities have opened up for demand-responsive control. Naturally, the newly developed technologies also require new control concepts to be developed. From the analysis conducted in Chapter 2, the following requirements for a demand-responsive control system have been derived (Section 2.5):

(1) The system shall provide better performance than off-line methods. This is obviously the primary criterion, but it has not been always recognized as such explicitly in past efforts.

(2) Needs development of new concepts and not merely the extension of existing concepts. As demonstrated by the experiments reviewed in this report, effective responsiveness is not achieved by just implementing off-

line methods at an increased frequency. New methods have to be developed.

(3) Be truly demand-responsive, i.e., adapt to actual traffic conditions and not to historical or predicted values that may be far off from the actual.

(4) Not be arbitrarily restricted to control periods of any length, but can be updated at any time, at any location.

(5) Is not encumbered by a network model structure that requires extensive centralized computer capability, but is decentralized in its decision-making and uses only those data that are directly pertinent to the decisions it has to reach.

(6) Obviates the conventional notions of offset, split, and cycle time, which are inherent in all existing signal optimization methods.

(7) The pattern of any individual signal should consist of a continuously varying, demand-responsive, sequence of ON (effective green) and OFF (effective red) times that are only subjected to appropriate lower and upper bounds.

The succeeding chapters describe the studies undertaken and the results achieved in laying the foundation for such a system. Chapter 3 describes the development of OPAC-1 (Optimization Policies for Adaptive Control), a Dynamic-Programming-based computer program that calculates globally optimal policies for adaptive signal control. While not suitable, by itself, for on-line implementation, it provides a very important standard for assessing the relative effectiveness of other strategies.

Chapter 4 describes a simplified method for calculating optimal policies for adaptive control (OPAC-2). This is a simplified version of the Dynamic Programming method and is based on optimal sequential constrained search (OSCO). It reduces (compared to DP)

flow information requirements by a ratio of 1:5 and 1:10 and running times by about 1:10 (to a total of 1.3 CPU-seconds per minute of real-time data). Nevertheless, the results it produces are very close to the optimal. Thus, it is shown, that OPAC-2 can be used as a basic building-block for demand-responsive decentralized control.

Chapter 5 further improves on the methodology established in Chapter 4. It introduces a rolling horizon strategy for implementing OPAC-2 (named ROPAC). This strategy derives demand-responsive control policies using readily available traffic flow information within a reasonable amount of computer processing time. Thus the ROPAC strategy creates a very promising candidate for real-time decentralized traffic control. The conclusions of the chapter provide an outline for the continuing research needs in further developing this strategy.

2. STRATEGY DEVELOPMENT AND TESTING: A REVIEW OF MAJOR EXPERIMENTS

In this chapter we review some of the major experiments with computer-controlled strategies that were conducted during the past dozen years in Great Britain, Canada, and the United States. We report and assess the results obtained from field testing of the strategies in view of our goals: the development of demand-responsive decentralized urban traffic control strategies. We use the nomenclature developed in the UTCS project to label the different types of strategies:

- 1-GC - First Generation Control (off-line optimization)
- 2-GC - Second Generation Control (on-line optimization, predicted flow values, stepwise steady-state flow conditions)
- 3-GC - Third Generation Control (on-line optimization, responsive control)

These concepts are explained in further detail below.

2.1 TRRL Experiments

A number of different strategies for controlling traffic signals in a network have been subjected to full-scale tests by the Transport and Road Research Laboratory (TRRL) in Great Britain. Most of the testing was carried out in Glasgow, where a computerized system of 80 traffic signals covering an area of about 3 sq. km. has been instrumented since 1967. The strategies that were tested fall broadly into three categories:

1. Fixed-time plans based on historical data and calculated off-line by a computerized optimization technique.
2. Strategies in which each signal can respond individually to traffic detected on the approaches, subject to some basic coordination scheme similar to (1).
3. Responsive strategies in which all the signal settings are calculated on-line using a real-time algorithm and information from detectors.

A brief description of the different strategies tested by the Laboratory are given in Table 2.1. A summary of their performance results is given in Table 2.2. The criterion used for comparison of the strategies is the total travel time (in vehicle-hours per hour) spent in the network, as related to the total amount of travel (total vehicle-kilometers per hour). Travel time data were collected by means of "floating cars" [7]. Sample plottings of results is given for the two responsive strategies (Figures 2.1 and 2.2), because they are of the most interest for the purposes of this study. Various aspects of the results are discussed below in light of our goals--the development of traffic-responsive strategies (reference is given to strategy numbers in Table 2.2).

Fixed-time plans

1.1 A systematic optimization technique (COMBINATION METHOD) is more effective than the existing city plan, especially since a variety of three different time-of-day plans are available to respond to the different traffic patterns existing in the area.

1.2 TRANSYT has undoubtedly a more detailed traffic model than CM, but CM has a better optimization procedure. The original version of CM used by TRRL is handicapped by the restriction on network structure and, therefore, is suboptimal. Implementation of the subsequently developed GCM (Generalized Combination Method) could have conceivably made up the small performance differences experienced in the tests [8].

1.3 SIGOP and TRANSYT produced equal rates of travel time in both Glasgow and San Jose, when tested under similar conditions (same cycle time). 'Double-cycle' TRANSYT (in which the less saturated signals run on half the cycle time used by the more heavily loaded signals) gave a 4 percent improvement in travel times when compared with 'single-cycle' TRANSYT. About half the signals in Glasgow were on 'double-cycle'. Presumably, SIGOP would have given similar results with a 'double-cycle' feature, which could be easily incorporated [9,10].

Adaptive strategies

2.1 Superimposing vehicle actuation on a fixed-time plan did not improve performance in Glasgow, because: (a) under moderate flows, what is gained by early release of traffic at one signal may be lost downstream; (b) under heavy flows, FLEXIPROG reverts to fixed-time operation. The version tested in West London permitted less variation in the green times than the one in Glasgow, and this feature may account for the differences in results (a 2% improvement).

2.2 In very light flows FLEXIPROG is effectively the same as an isolated vehicle-actuated system. Again, any benefits gained by the greater variability locally are apparently dissipated by the lack of structure in the network [1].

2.3 Reasons why EQUISAT showed no improvement over fixed-time include the following: (a) the three CM plans had already been carefully selected to suit the average conditions for the periods being studied; (b) undersaturated intersections are unlikely to benefit from redistribution of green times--perhaps 75% of the signals in the center of Glasgow were sufficiently undersaturated to be unaffected by EQUISAT [1].

Responsive strategies

3.1 To improve on an optimized fixed-time strategy, the dynamic plan generation strategy has to carry out all the following steps on-line: (a) predict the flow pattern in the immediate future; (b) calculate good optimized settings from the predictions; (c) change the signal timings to a new optimized plan with the minimum of disturbance. While the installation in Madrid executed all of those steps, the concept as a whole failed to produce the desired results. Changing signals to minimize the PI over successive short intervals (of a few minutes), does not necessarily optimize performance over a longer period. Many reasons are contributing: prediction is, generally, inaccurate; optimization has to be simplified in order to be fast; and, lastly, losses in transition are not

sufficiently recompensed by possible gains in responsiveness if the changes are too frequent [6].

3.2 There is little doubt that PLIDENT was working as intended. The strategy was extremely flexible, and, to accommodate the observed traffic, cycle times at an intersection could vary from the minimum of about 45 seconds to upper bounds of about 5 minutes. There appeared to be relatively less delay on the priority routes than on the non-priority routes although the priority routes were still substantially worse under PLIDENT than with fixed-time settings. These results should be of no surprise at all. One cannot expect to minimize total travel time when the explicit objective of the strategy was to provide uninterrupted movement to a small subset of the vehicles travelling on the network. The two objectives are not compatible [5].

As a result of these experiments, TRRL concluded that the most effective strategy is to operate the traffic control system on a fixed-time basis using a library of signal timing plans that were prepared off-line based on historical data.

2.2 The Toronto Experiments

An extensive study of the effectiveness of various control strategies was conducted in Metropolitan Toronto [12]. In total, four different strategies were evaluated with respect to an EXISTING strategy, which was based on an arterial preference method named SIGRID. The first three strategies were the same 1-GC strategies tested by TRRL. The fourth was a locally-developed 2-GC strategy, RTOP (Real-Time Optimization Program).

RTOP computes optimal signal timing parameters on a real-time basis for successive 15-minute control periods. This period was chosen as a compromise between the requirements of responsiveness and the disruption caused by timing-plan switching. A range of possible common cycle lengths and corresponding splits is calculated by Webster's method. Offsets are then calculated by a fusion

of COMBINATION-type LFP's and a SIGOP-derived gradient optimization, for each of these cycles. The settings that produce the lowest value of the system PI is chosen for implementation.

A volume prediction model is a key component of the package. The model predicts for each 15-minute control period (CP) traffic volumes for each detectorized link taking into account three prediction components: historical volume trends (day-to-day), current volume trends (CP-to-CP), and directional relationships (volume trends on a representative link). As illustrated in Figure 2.3, a finite time is required to complete the prediction process and the subsequent optimized settings; therefore, a considerable time lapse is inevitable between real time data acquisition and signal timing implementation. To provide a set of optimized signal timings for implementation in the (n+1)th control period, the necessary prediction computations must be completed in the n-th control period, using data accumulated at the end of the (n-1)th interval. The generated signal settings are therefore at least two intervals behind the actual traffic volume measurements. Furthermore, the entire prediction procedure, including all the necessary data smoothing and evaluation, spans over four control periods. Thus, it takes at least four intervals from the start of data collection to complete the initialization process for the prediction model.

Field evaluations were conducted in two distinctly different locations in terms of traffic behavior. The first was a CBD arterial-based 2.5 x 1.5 mile grid network containing 68 signals. However, only two intersecting arterials with 24 signals were included in the RTOP test because of computer processing capability limitations. The second was a suburban 3.5 x 2.5 mile grid within a major freeway corridor with 51 traffic signals. Results are summarized in Table 3, which indicates that among the 1-GC strategies, COMBINATION showed a modest superiority in reducing total travel time in both locations. The results for the RTOP-strategy were mixed: it surpassed the performance of the existing plan in the CBD-grid (equal to that of CM), but was less effective in the suburban-grid. The main reasons for that were thought to be:

(a) Traffic fluctuations in the suburban area are generally more rapid, but shortlived in nature, than the central area. The 15-minute traffic prediction subroutine in RTOP could not often cope with the rapid trending of volumes.

(b) The suburban area consists of twice as many signals as the central area, thus posing a more severe demand on the offset optimization process. As a result the process had to be compromised on occasion, in order to save computation time.

TABLE 2.3: SUMMARY OF TORONTO EXPERIMENTS (total travel time)

Strategy	CBD	SUBURB
SIGOP	Equivalent to EXISTING	EXISTING better by 3.2%
TRANSYT	Equivalent to EXISTING	EXISTING better by 2.5%
COMBINATION METHOD	4.5% better than EXISTING	2.8% better than EXISTING
Real-Time Optimization Program (RTOP)	4.8% better than EXISTING	EXISTING better by 6.3%

Table 2.1: Description of TRRL Strategies [1]

1. Fixed-time plans

The three techniques tested under this category are designed to calculate offsets in a network so as to minimize a performance index (PI). The common cycle time as well as the splits at each intersection are calculated apriori; sub-multiple cycles can be accommodated if justified. The PI can be any combination of delays and stops; delays only were used in Glasgow. [All three methods are in the 1-GC category.]

1.1 COMBINATION METHOD (CM) - Traffic performance is represented by a link performance function (LPF) which relates platoon delay on each link to the offset across that link. The PI is separable since the LPF does not depend on other offsets in the network. A dynamic programming principle is used to determine the optimum. The network structure is restricted to be of the series-parallel type [2].

1.2 TRANSYT - This method uses a simple but effective model of traffic flow which includes allowance for turns, platoon dispersion, and flow interaction between successive links of the network. An iterative search technique is used to minimize the PI, in which one node offset is considered at each step. Splits can also be included in the optimization [3].

1.3 SIGOP - Similar to COMBINATION, uses a standard LPF in which delay vs. offset is represented by a parabolic curve. The bottom of the parabola is positioned at the ideal offset value for that link. Optimal offsets are determined by a gradient minimization technique. All signals are assumed to have the same cycle, but several cycles are evaluated in one computer run [4].

2. Coordinated systems with local traffic response

The two techniques tested in this category use either COMBINATION or TRANSYT for the underlying coordination, and information from pneumatic detectors for local adaptation. [1-GC with CIC.]

2.1 FLEXIPROG (a vehicle-actuated flexible progressive system) - As long as there is a continuous flow of traffic over all detectors, the signals change according to the underlying fixed-time system. When traffic is lighter the signals can change after a suitable gap occurs. Phases can be skipped if there is no demand on them [5].

Table 2.1 (Cont'd)

2.2 EQUISAT (equal degree of saturation) - Cycle times and phasing are fixed; the offset of the middle of one green at each signal is fixed according to the underlying fixed-time strategy. Allocation of green time is varied to equalize a smoothed average of the degree of saturation on each phase [5].

3. Responsive strategies

3.1 DYNAMIC PLAN GENERATION - A common cycle time and splits are calculated by Webster's method using smoothed estimates of flow on each approach. Offsets are calculated to minimize delay or stops using measured or estimated speeds and simple model of traffic flow; only non-looped strings of intersections can be considered. Settings are recalculated every 3 cycles; however, up to 1.5 cycles may be required for transition [6]. [2-GC strategy.]

3.2 PLIDENT (platoon identification scheme) - This scheme has no formal cycle time or linking; it attempts to identify the movement of platoons of traffic on the road network and, by predicting arrival times, aims to operate the signals so as to process the platoons unimpeded on certain priority routes. Only one approach per signal can be assigned priority and its green time is adjusted according to the estimated platoon length from upstream data [5]. [3-GC strategy.]

Table 2.2: Summary of TRRL Test Results [5,7]

Strategy	Main tests	Main results	Other tests
1. Fixed-time plans			
1.1 Combination Method (CM)	Compared with the system existing in Glasgow which was vehicle-actuated, linked on the major routes, with a single plan for the whole day. Three CM plans were tried for a.m. peak, off-peak and p.m. peak.	CM gave consistently shorter travel times with all three plans (average 12 per cent).	Similar test in West London gave similar results (average 9 per cent, not significant).
1.2 TRANSYT	Compared with CM for three plans; peak, off-peak and p.m. peak.	TRANSYT gave consistently shorter travel times with all three plans (average 4 per cent).	Similar test in West London gave similar results (average 2 per cent, not significant).
1.3 SIGOP	1) Compared with TRANSYT for three plans: a.m. peak, off-peak and p.m. peak. 2) As above with TRANSYT using half cycles where appropriate.	1) No measurable difference in travel time with any plan. 2) No measurable difference in a.m. peak; SIGOP gave longer journey times for other two plans (average 4 per cent).	Similar test in San Jose gave similar results.
2. Locally adaptive strategies			
2.1 FLEXIPROG	Strategy with CM for the basic linking, compared with the same fixed-time CM settings for three plans: a.m. peak, off-peak and p.m. peak.	No measurable difference in travel times with any plan.	Slightly different version of FLEXIPROG in West London gave a slight improvement (2 per cent, not statistically significant).

Table 2.2 (Cont'd)

2.2	Isolated Vehicle Actuation	Compared with TRANSYT under very light flow conditions between 0100 and 0300 a.m.	No measurable difference in travel times with both strategies.
2.3	EQUISAT	Strategy with CM for the basic linking, compared with the same fixed-time CM settings for three plans; a.m. peak, off peak and p.m. peak.	No measurable difference in travel times with any plan.
3.	Responsive Strategies		
3.1	Dynamic Plan Generation	Compared with fixed-time strategy using hill climb technique similar to TRANSYT in Madrid. Three different fixed-time plans compared during four periods of the working day, including the peak periods.	Dynamic signal plan generation gave consistently longer travel times (average 9 per cent).
3.2	PLIDENT	Three different CM plans used for comparison during a.m. peak, off-peak and p.m. peak.	PLIDENT gave consistently longer travel times (average 29 per cent).

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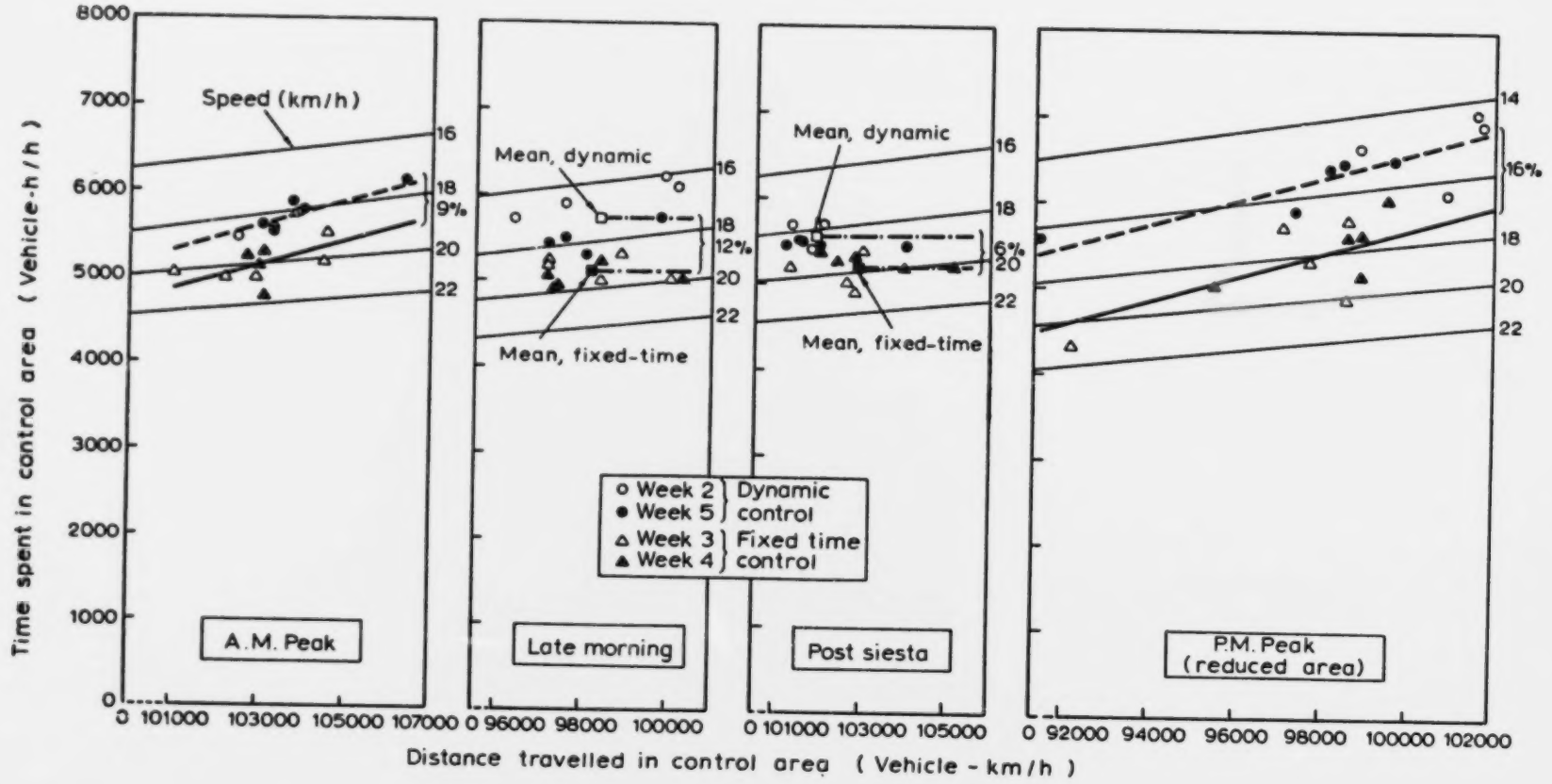

Figure 2.1: COMPARISON OF DYNAMIC PLAN GENERATION AND FIXED TIME CONTROL SYSTEM IN MADRID [6].

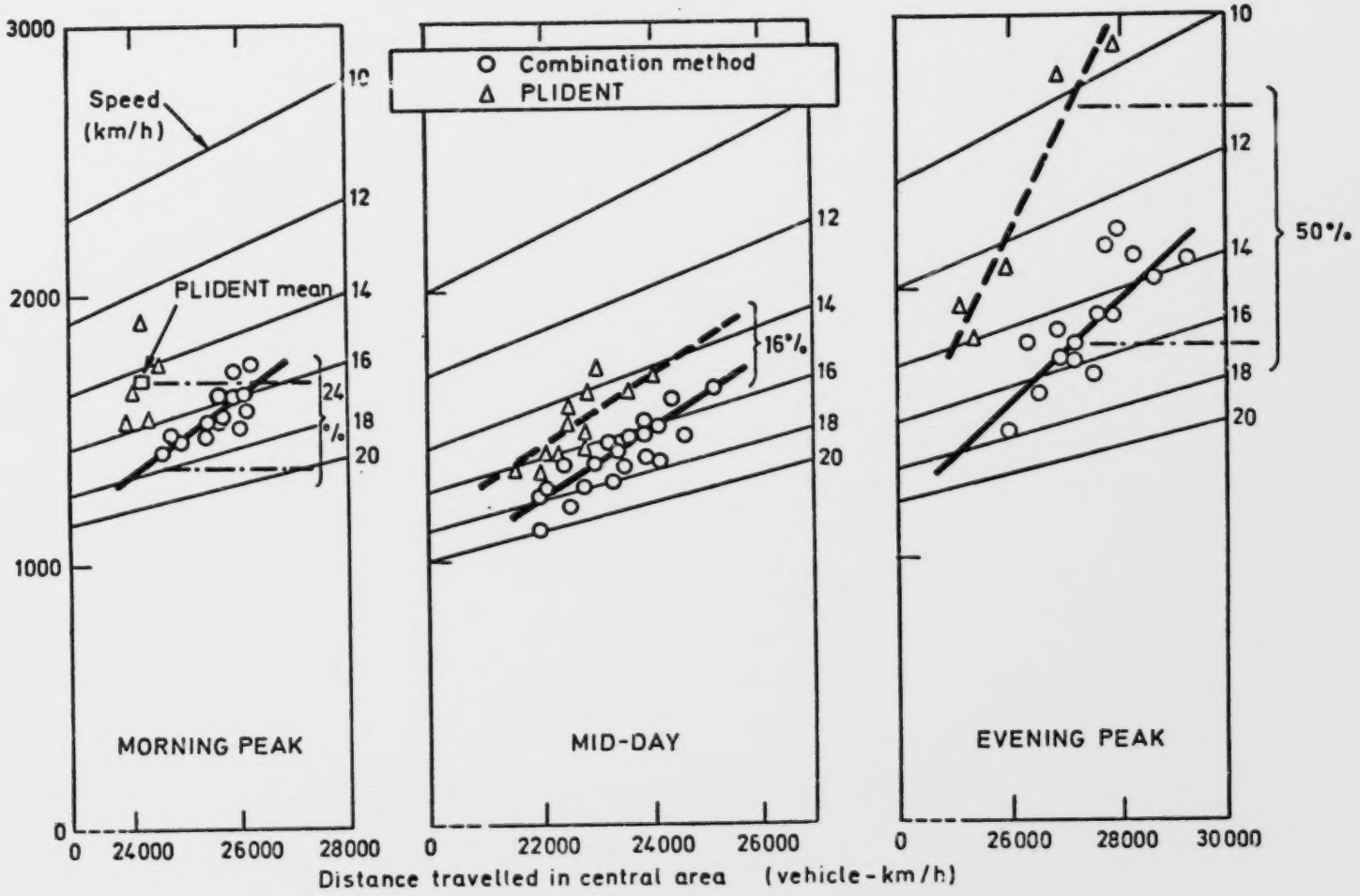

Figure 2.2: COMPARISON BETWEEN PLIDENT AND COMBINATION METHOD [5].

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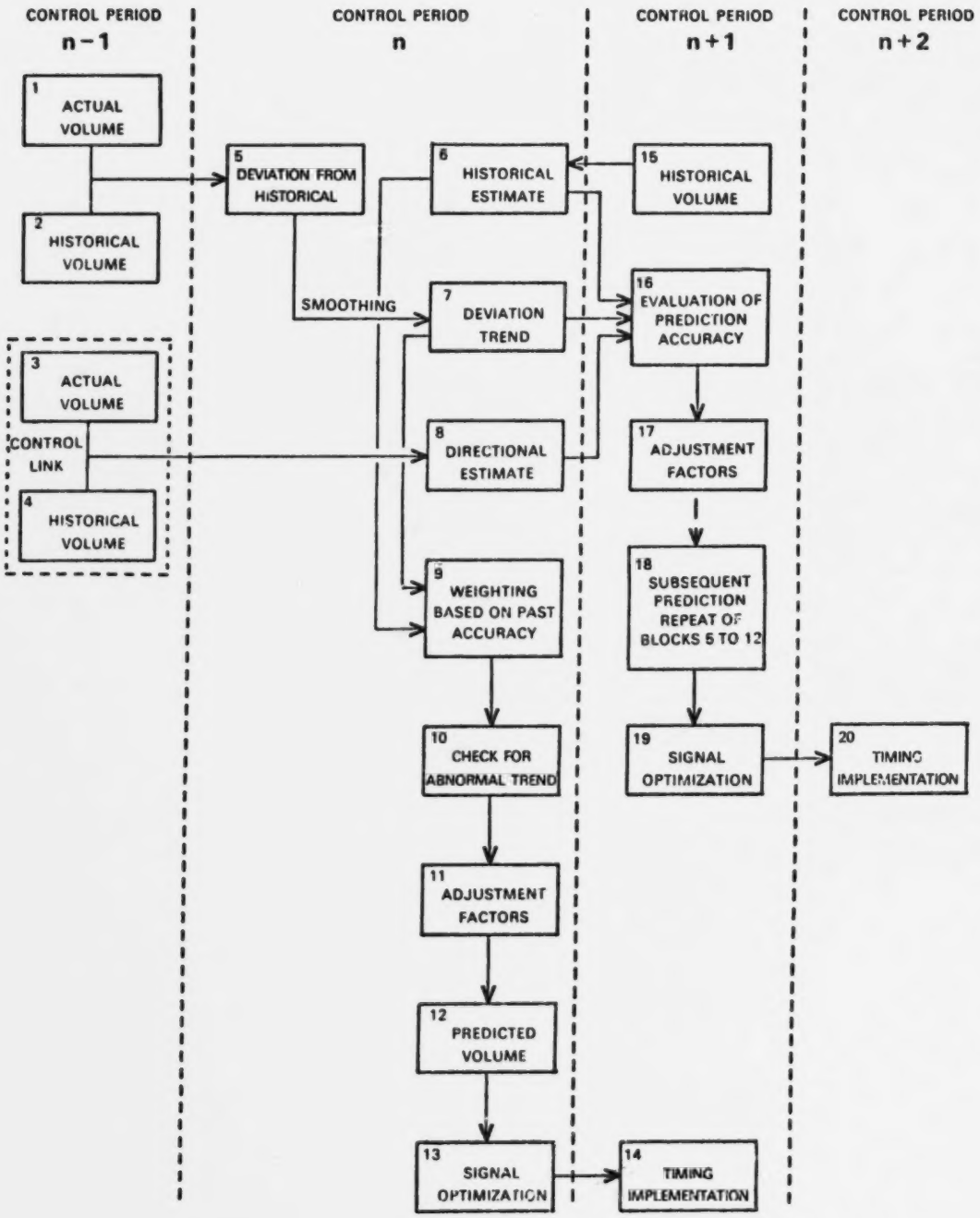

Figure 2.3: Traffic prediction and optimization process in RTOP [11].

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2.3 The Urban Traffic Control System [12]

In recognition of the significant advances of the state-of-the-art in both software and hardware offered by computer control systems, the U.S. Department of Transportation (DOT) initiated in 1967 the Urban Traffic Control System (UTCS) research project. It involved a 200-intersection computerized test system in Washington, D.C., consisting of arterials and a grid network containing 512 vehicle detectors, and extensive data processing, communications, and display equipment. The project was directed toward the development and testing of a variety of network control concepts and strategies and lasted for almost a decade.

Research and testing of control strategies in the UTCS project was divided into three generations, as shown in Table 2.4. The different generations can be characterized as follows:

First-Generation Control (1-GC) - This mode of control uses prestored signal timing plans which are calculated off-line based on historical traffic data. The plan controlling the traffic system can be selected

TABLE 2.4: Characteristics of UTCS Control Strategies

FEATURE	FIRST GENERATION	SECOND GENERATION	THIRD GENERATION
Update interval (Control Period)	15 minutes	5-10 minutes	3-5 minutes (Variable)
Control plan generation	Off-line optimization selection from library by time-of-day, traffic responsive, or manual mode (7 plans used)	On-line optimization	On-line optimization
Traffic prediction	None	Historically based	Smoothed values
Critical intersection control (CIC)	Fine tuning of splits	Fine tuning of splits and offsets	Not applicable
Cycle length	Fixed within each section	Fixed within variable groups of intersections	Variable in time and space Predetermined for control period

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on the basis of time-of-day, by direct operator selection, or by matching from the existing library a plan best suited to recently measured traffic conditions (volumes and occupancies). Frequency of update is 15 minutes. 1-GC-software also includes logic to enable a smooth transition between different signal timing plans, and a critical intersection control (CIC) feature which enables vehicle-actuated adjustment of green splits at selected signals. Plans can be calculated by any off-line signal optimization method, TRANSYT-generated plans were selected for testing in UTCS [13].

Second-Generation Control (2-GC) - This is an on-line strategy that computes in real-time and implements signal timing plans based on surveillance data and predicted values. The optimization process is repeated at 5-minute intervals; however, to avoid transition disturbances, new timing plans cannot be implemented more often than every 10 minutes. 2-GC software contains the following features:

- Optimization algorithm - the OPTIMIZ module of the SIGOP program was selected because of its short execution time and moderate computer storage requirements.
- Traffic prediction model - to provide estimates of volume and speed as a function of historical values (time-of-day) and recently measured trends.
- Subnetwork configuration models - to improve optimization effectiveness by dynamically configuring the signals into subnetworks on the basis of prevailing traffic conditions. Each subnetwork has a common cycle time.
- Critical intersection control (CIC) - splits and offsets can be adjusted at selected signals, once per cycle, as a function of the demand (computed values of queues and volumes on the approaches).
- Transition model - to minimize transition time between two plans.

Third-Generation Control (3-GC) - This strategy was conceived to implement and evaluate a fully responsive, on-line traffic control system. Similar to 2-GC it computes control plans to minimize a network-wide objective using for input predicted traffic conditions. The differences compared to 2-GC are that the period after which timing plans are revised is shorter (3-5 minutes), and that cycle

length is required (a priori) to vary among the signals as well as at the same signal during the control period (CP). This is done by dividing the CP into an integral number of intersection-specific control intervals (CI), which is calculated based on the predicted volume/capacity ratios on each approach to the intersection using a Webster-like method. Thus, the CI's approximate expected values of cycle lengths. However, the switching points within each CI vary and are determined by the optimization procedure. This procedure, termed CYRANO (cycle-free responsive algorithm for network optimization), is a variable-cycle variant of the fixed-background-cycle optimization program SIGOP II [14]. In this method, a simplified model of traffic flow scenarios is used to trace performance, in an iterative manner, through strings of mini-star networks composed of the signal and all its incoming and outgoing links.

The dynamics of control plan generation and implementation for the three UTCS strategies is illustrated in Figure 2.4. It is noteworthy that 3-GC is very similar in concept to 2-GC. In both strategies the traffic data used in the timing plan that is being implemented are displaced by at least two intervals from the actual flows. The different UTCS control strategies were designed to provide an increasing degree of traffic responsiveness, expecting to capitalize on the variability in traffic flows and to improve urban street network performance. However, results of extensive field testing showed that these expectations were not entirely fulfilled [12,15].

1-GC, in its various modes of operation, performed overall best and demonstrated that it can provide some measurable reductions in total travel time over that which could be attained with a well-timed three-dial system. The traffic-responsive mode of 1-GC plan selection is generally more effective than the time-of-day mode. 2-GC had a mixed bag, but was overall inferior compared to 1-GC; it demonstrated some small improvements on the arterial, but degraded traffic flow in the network. These results are generally consistent with those experienced in Toronto (and in San Jose with the ASCOT logic [16]). 3-GC, in the form tested in the UTCS system, seriously degraded traffic

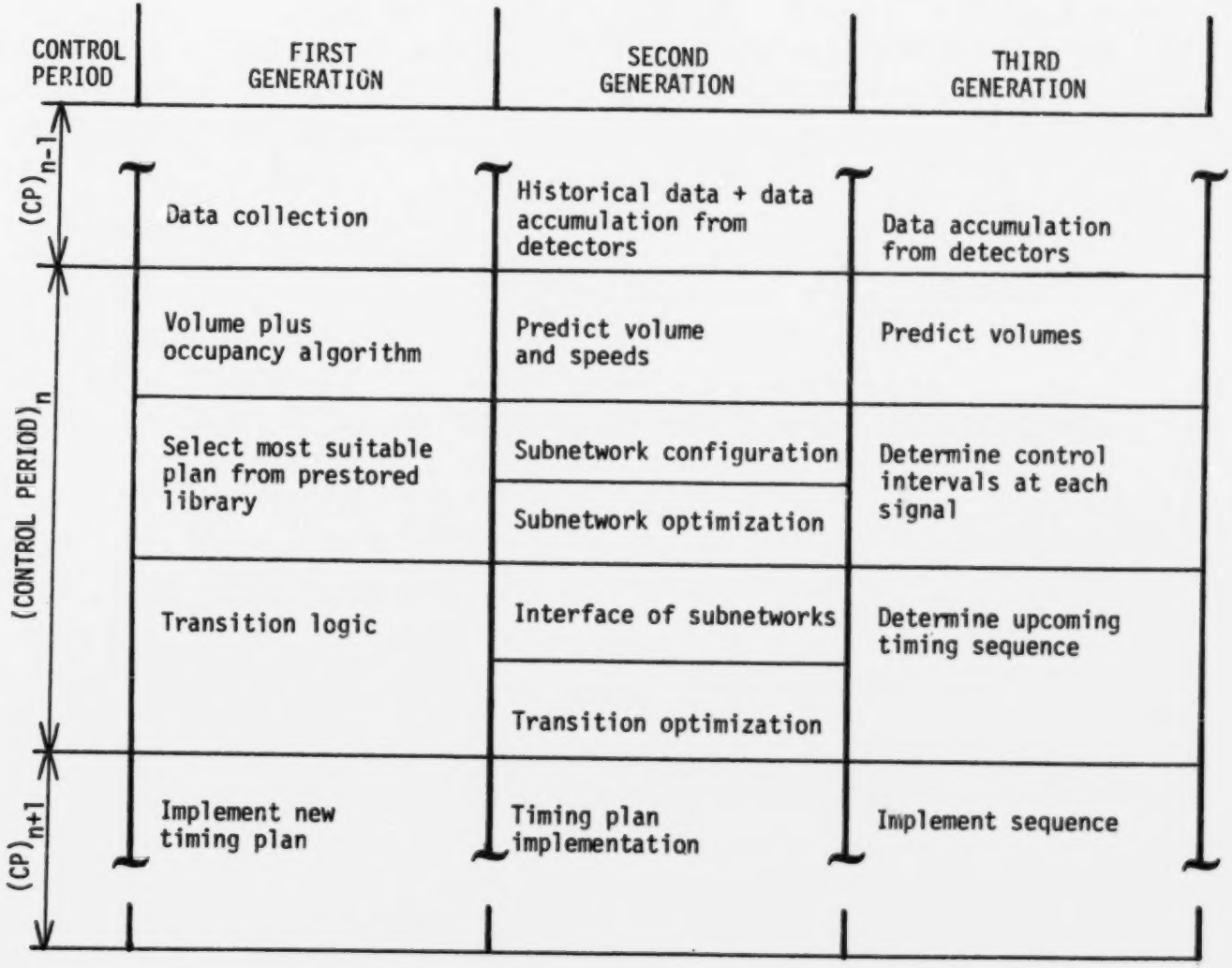

Figure 2.4: Dynamics of control plan generation and implementation in the UTCS strategies

flow under almost all the conditions for which it was evaluated. It worked worst when it was supposed to work best--the arterial off-peak period. A summary of the results is given in Table 2.5.

TABLE 2.5: COMPARISON OF RESULTS OF UTCS CONTROL STRATEGIES (4)

Traffic Responsive Strategy	Percent change in aggregate vehicle-minutes of travel with respect to base			
	A.M. Peak	Off Peak	P.M. Peak	All Day Average
First Generation (traffic responsive)				
Arterial	-2.6	-4.0	-12.2	Not
Network	-3.2	+1.9	- 1.6	Available
Second Generation				
Arterial	-1.3	-3.8	+ 0.5	-2.1
Network	+4.4	+1.9	+10.7	+5.2
Third Generation				
Arterial	+9.2	+24.0	+21.2	+16.9
Network	+14.1	-0.5	+ 7.0	+8.2

Some of the reasons for the poor showing of the responsive strategies are thought to be the following:

(a) Because of the inherent inaccuracies in the measurement-prediction cycle, neither 2-GC nor 3-GC can respond adequately to rapid changes in flows.

(b) The frequent transition in signal timing may be more harmful than the adaptation sought by on-line optimization (2-GC and 3-GC). For an analysis of delays incurred during transition see References [17,18].

(c) While 3-GC has a variable-cycle feature, the entire signal switching sequence is predetermined for every control period and, therefore, not responsive to actual changing traffic conditions on the street. In essence, it is a 2-GC strategy with variable cycle. Furthermore, the variable-cycle timing is not an output of the optimization but a requirement imposed on it; hence it is not necessarily conducive to improved performance.

(d) The control strategy used by 3-GC is centralized and its optimization requires a relatively long time for convergence (much longer than 2-GC for the same size network). Because of the prescribed dynamics of 3-GC, the time allotted for this procedure is insufficient for reaching a good optimum.

2.4 An Assessment

From the studies cited above, one may erroneously conclude that a library of timing plans generated off-line, based on historical data (from another day, another month, perhaps another year--but for the same time period of the day), is more effective than timing plans generated on-line, based on very recent data (past 15 minutes, or 5 minutes, or 3 minutes). [This assessment is based solely on traffic performance. It does not consider other factors, such as on-line/off-line tradeoffs: 2-GC-type strategies may be less data and manpower intensive than 1-GC in the long-run, but require more surveillance equipment, etc.]. However, a closer examination of those studies reveals that the expectations of the researchers were not fulfilled not because this rationale is wrong (that traffic-responsive control should provide benefits over fixed-time control), but because of a failure of the models and procedures which were implemented to deliver the desired results.

Most available traffic control methods claim to be "traffic-responsive" in some sense. Even 1-GC strategies are traffic-responsive to a certain extent: control plans may be replaced at 15-minute intervals in response to expected traffic volume and occupancy trends. But, these methods are not truly responsive: they do not respond to actual traffic conditions, but to hypothetical conditions--the hypothesis being only as good as the model and the predictions used in the optimization are. This is the crux of the problem. The traffic flow process and the optimization procedure form an inseparable closed-loop control system; see Figure 2.5A. The control values can only be effective if an accurate model is used in the optimization. However, all the different-generation control strategies do not have an accurate

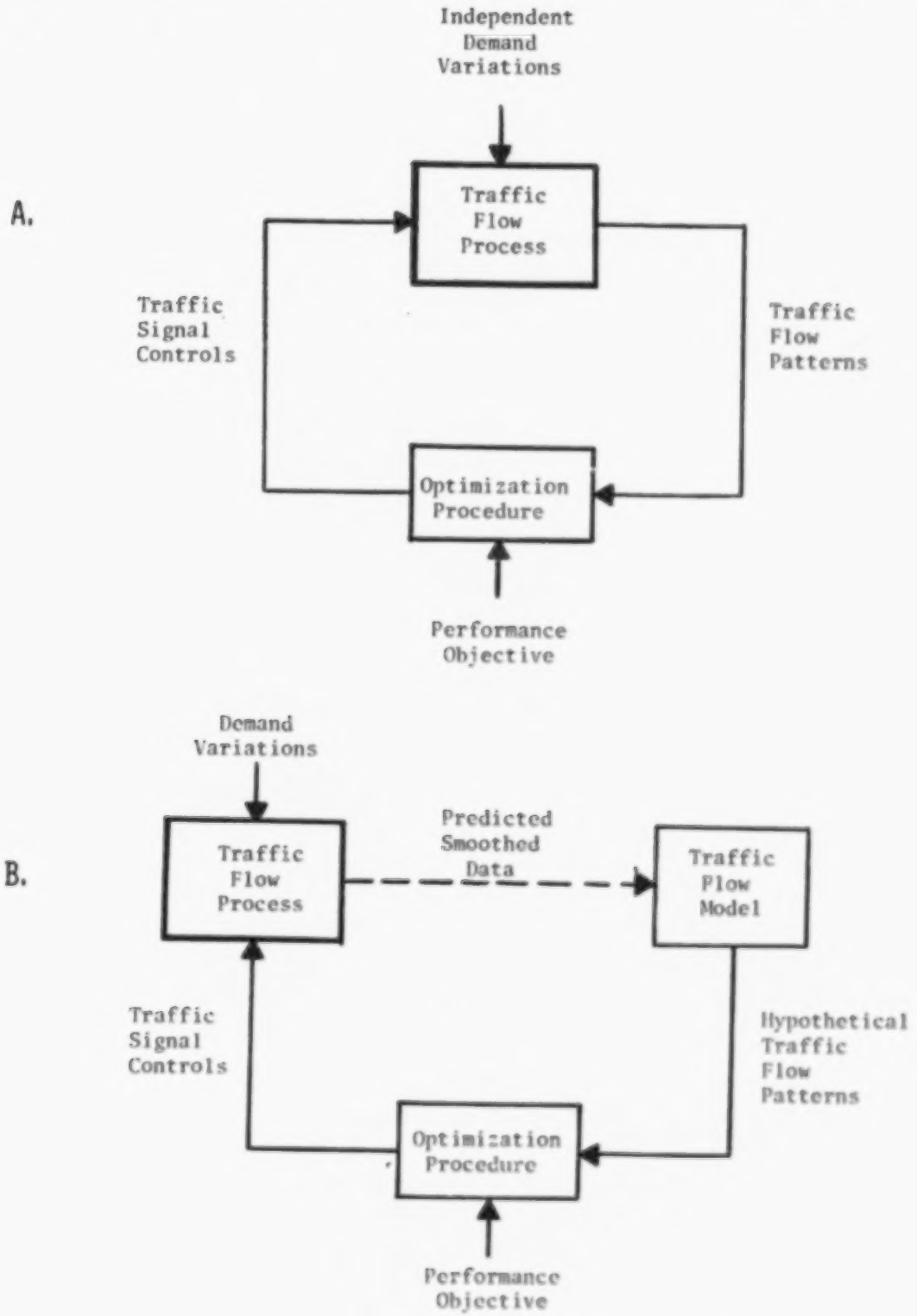

Figure 2.5: Schematics of traffic flow process control system.

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model; they use an abstract model (i.e., computer-generated) which is calibrated by predicted (thus, inherently inaccurate), aggregated (into flows/interval units), and smoothed (from one control period to another) volume data. Moreover, because of the dynamics of the strategy generation measurements lag by two control periods behind predictions (Figure 2.4). See Figure 2.5B for the resulting information flow schematics. Such a model cannot take account of any short-term fluctuations (such as of a few minutes, or fractions of minutes) which are typical of signal-controlled road networks and to which they are supposed to respond. In essence, by aggregating and smoothing the data, the information content which is most important for on-line demand-responsive control is destroyed.

Since the traffic-responsive strategies (2-GC and 3-GC) totally rely on predictions, let us examine briefly the quality of predictions that are obtained. Figures 2.6 and 2.7 show a comparison between measured and 2-GC predicted volumes for a "regular" day (i.e., conforming to historical time-of-day trends) and a "perturbed" day (i.e., deviating from the historical trends). The data were collected on a major arterial (N-190, near the intersection with N-308) in the center of Poissy (within the Paris metropolitan region) during a 10-hour period between 1 p.m.-11 p.m. [19]. Since the 2-GC predictor is historically-based it is apparent that there are increasing deviations on a "perturbed" day, when flows do not follow the expected pattern. However, even on a "regular" day the discrepancies between predicted and measured volumes are very substantial, often exceeding 30% of the measured value, sometimes even exceeding 50%. It is apparent that it is very difficult to derive meaningful traffic-responsive strategies with such noisy information as input.

To overcome the reliance on historical information, with the intention of producing predictions that are more attuned to actual flows, a 3-GC predictor was developed which uses only measured and smoothed volumes. An example of its performance compared to that of the 2-GC predictor and the measured volumes is shown in Figure 2.8

(from Reference [20]) for 5-minute intervals. Here, again, we see that there are wide discrepancies between measured and predicted volumes. The discrepancies are larger for the 3-GC predictor (even though it employed only one-step-ahead predictions, instead of the required two-steps-ahead) than for the 2-GC predictor, indicating the importance of the historical information content. When aggregated over shorter than 5-minute periods the discrepancies are exacerbated. Figures 2.9 and 2.10 show results of predictor-derived versus measured volumes at two signals (one coordinated and one isolated) on a cycle-by-cycle basis (from reference [21]). The best predictor in these cases, judged by the mean error value, turns out to be a moving-average algorithm. A most telling example is given in Figure 2.10 where the best predictor turns out to be an almost fixed value, the average flow, notwithstanding the highly variable cycle-by-cycle flow rates. It is quite clear that one cannot conceivably derive a traffic-responsive strategy from such a prediction. A comparative analysis of traffic-responsive versus time-of-day strategies concludes that

> ". . . vehicle detectors in combination with a good predictor algorithm provide very little additional information on conditions in a street network over simple historical averages" [22].

It is worthwhile, in this context, to examine a record of actual vehicle arrivals on a signal-controlled street. Such a record, for a 15-minute period, is given in Table 2.6 (from reference [23]). We see considerable short-term variations in demand (within cycles and between cycles), while there is almost no change in demand over successive 5-minute periods. Aggregation of the arrival data muffles the time-variations, thus eliminating any potential for effective responsive control. This also leads to the following observation: suppose one could predict the flows in each cycle with complete accuracy (i.e., with a zero mean error value). Even then the resulting real-time control strategy might be ineffective. For example, the following numbers represent vehicle arrivals for two cycles,

grouped into 5-second intervals, on a signal-controlled approach with a 60-second cycle-time:

1	1	2	1	1	2	0	2	0	0	1	1
0	1	0	0	1	1	2	1	2	1	1	2

During both cycles the flow is the same (12-vehicles), yet the optimal control strategy for each should be entirely different because of the different distribution of the arrivals within the cycle.

Clearly, an effective demand-responsive traffic control system requires the development of entirely new concepts and not merely the extension of existing concepts toward shorter time frames (i.e., going down from hourly intervals to 15-minutes, 5-minutes, 3-minute intervals, or a cycle time), and using predicted values that are less and less reliable. Data from detectors provide information about <u>past</u> traffic behavior while a traffic-responsive system must make decisions which result in good control in the <u>future</u>. Thus, ways must be devised to predict future traffic behavior from past detector measurements.

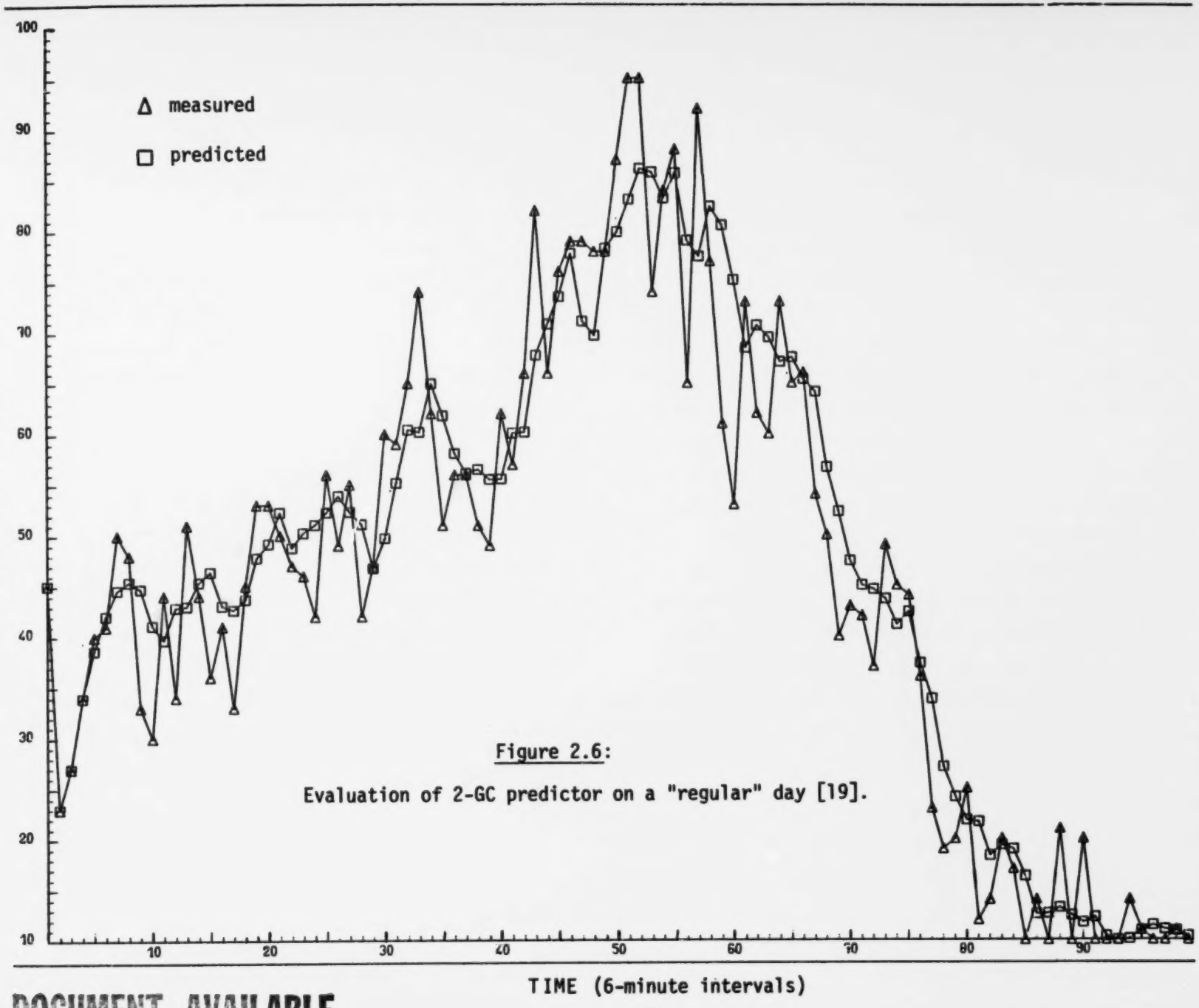

Figure 2.6:

Evaluation of 2-GC predictor on a "regular" day [19].

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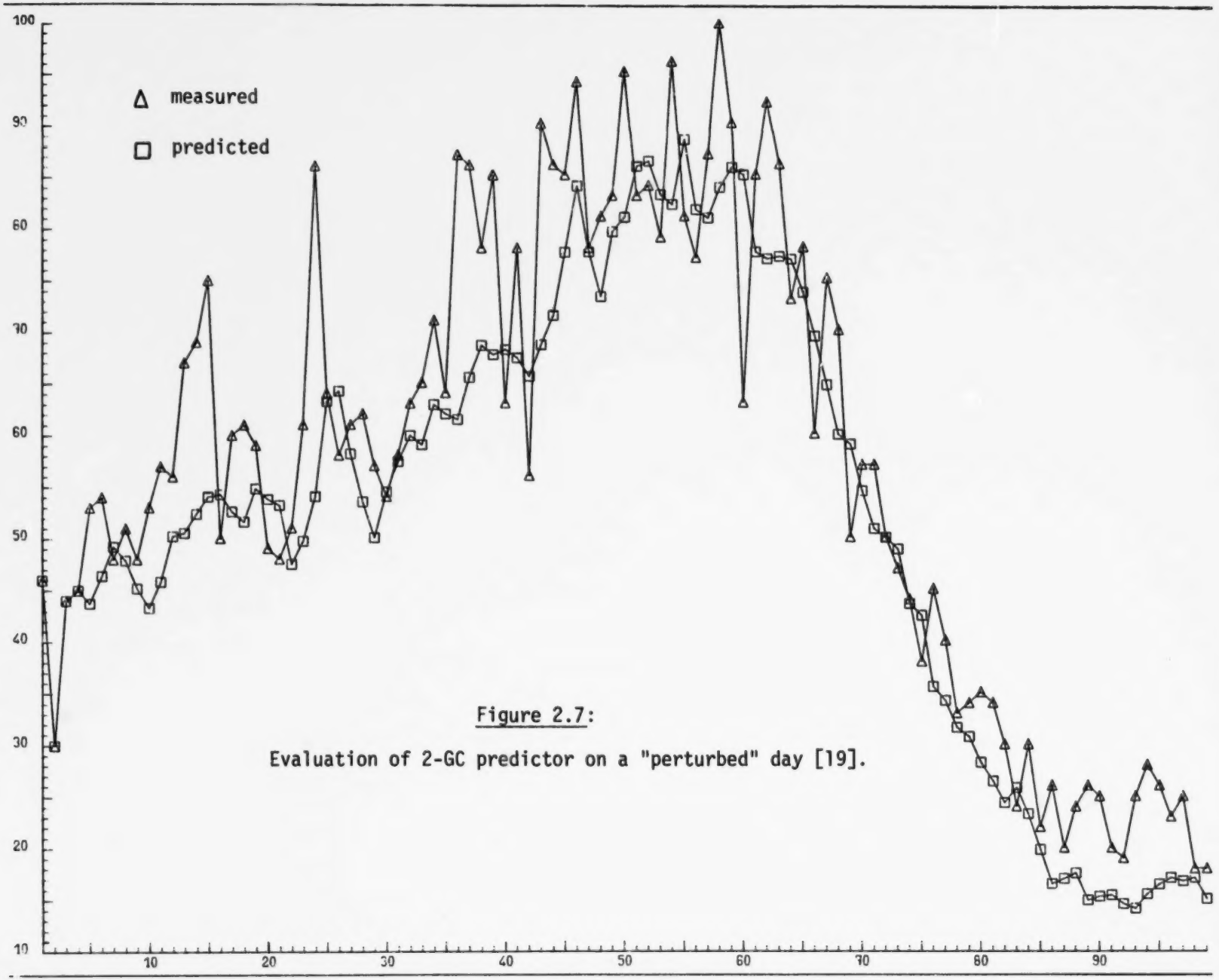

Figure 2.7:

Evaluation of 2-GC predictor on a "perturbed" day [19].

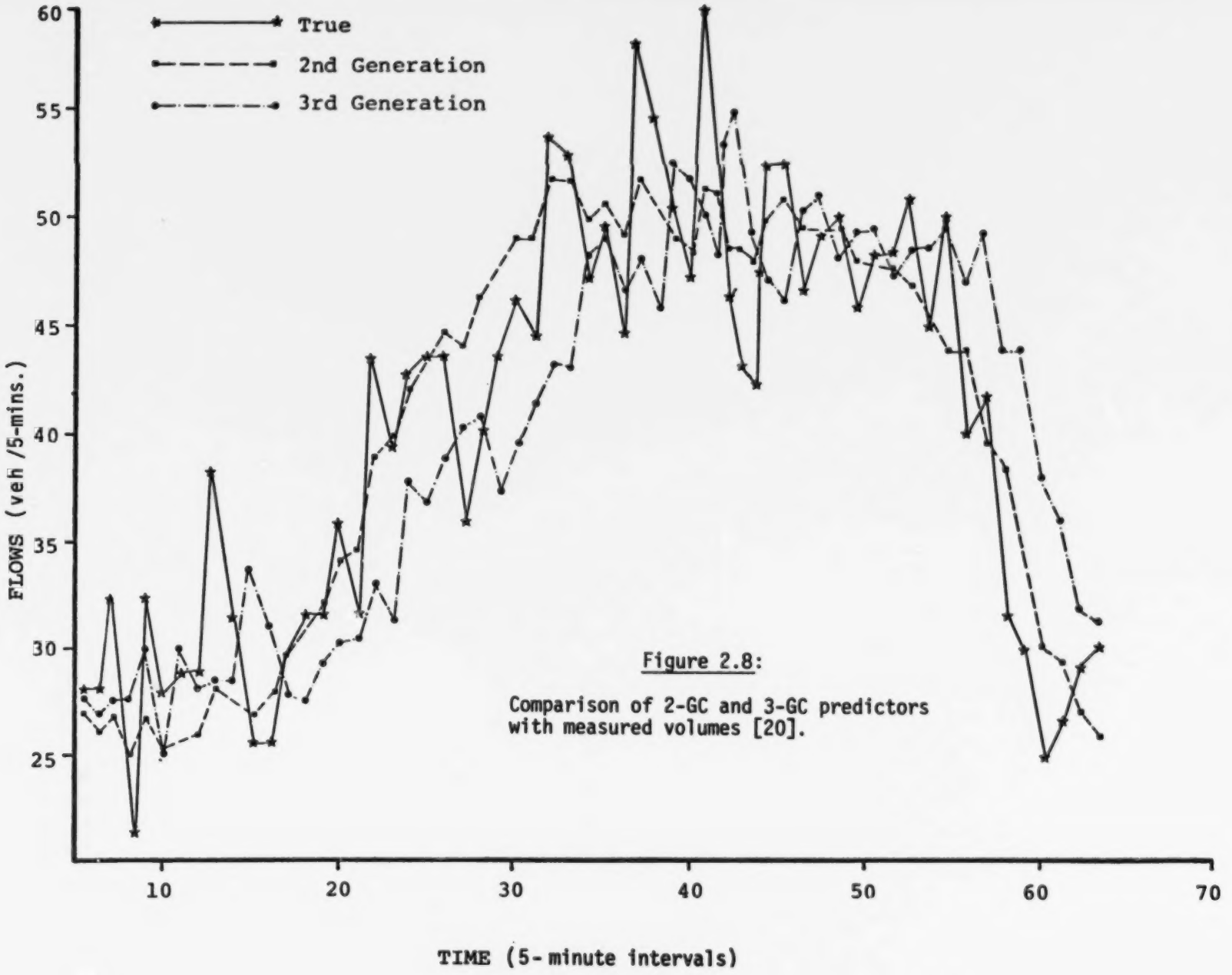

Figure 2.8:

Comparison of 2-GC and 3-GC predictors with measured volumes [20].

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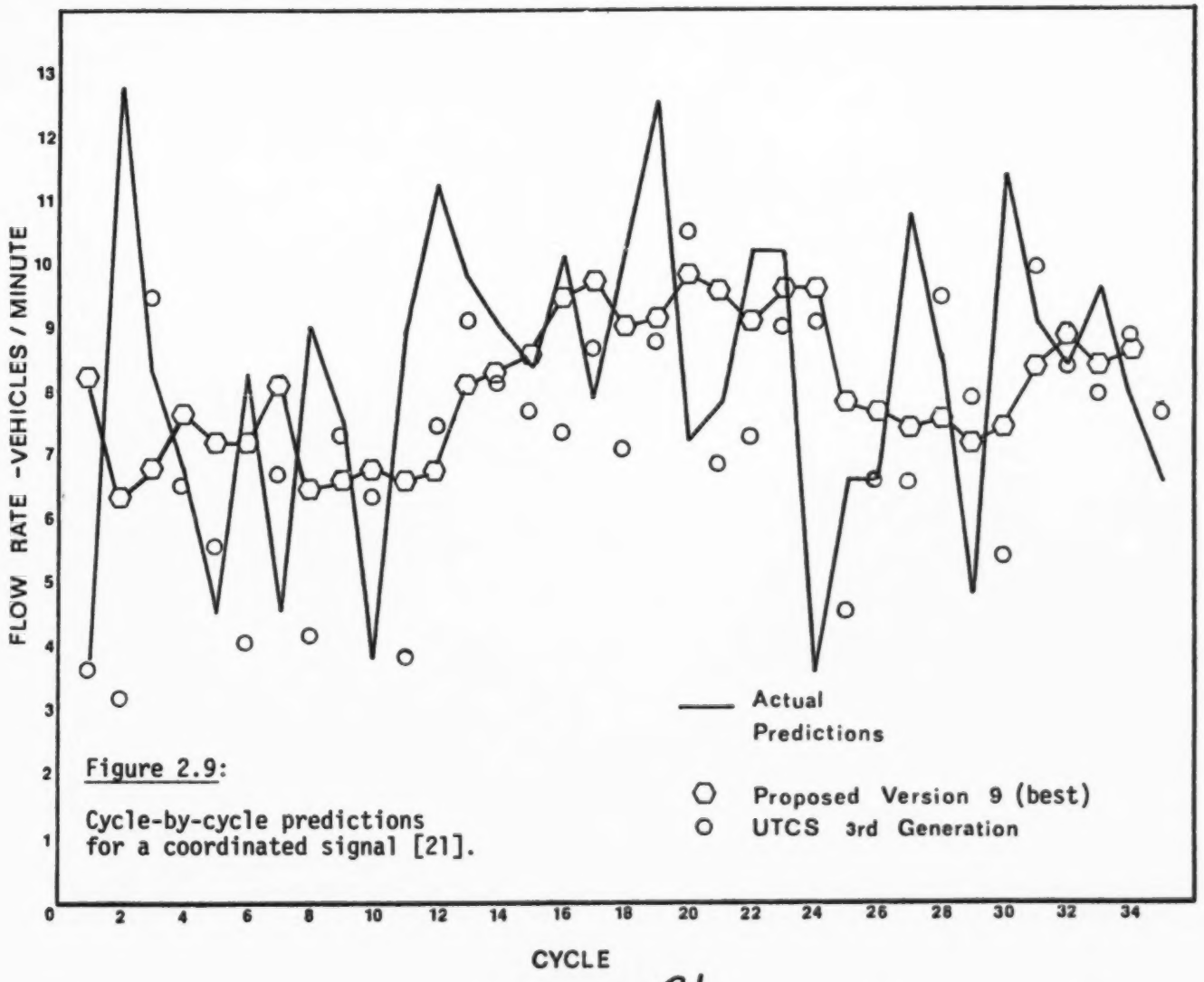

Figure 2.9:

Cycle-by-cycle predictions for a coordinated signal [21].

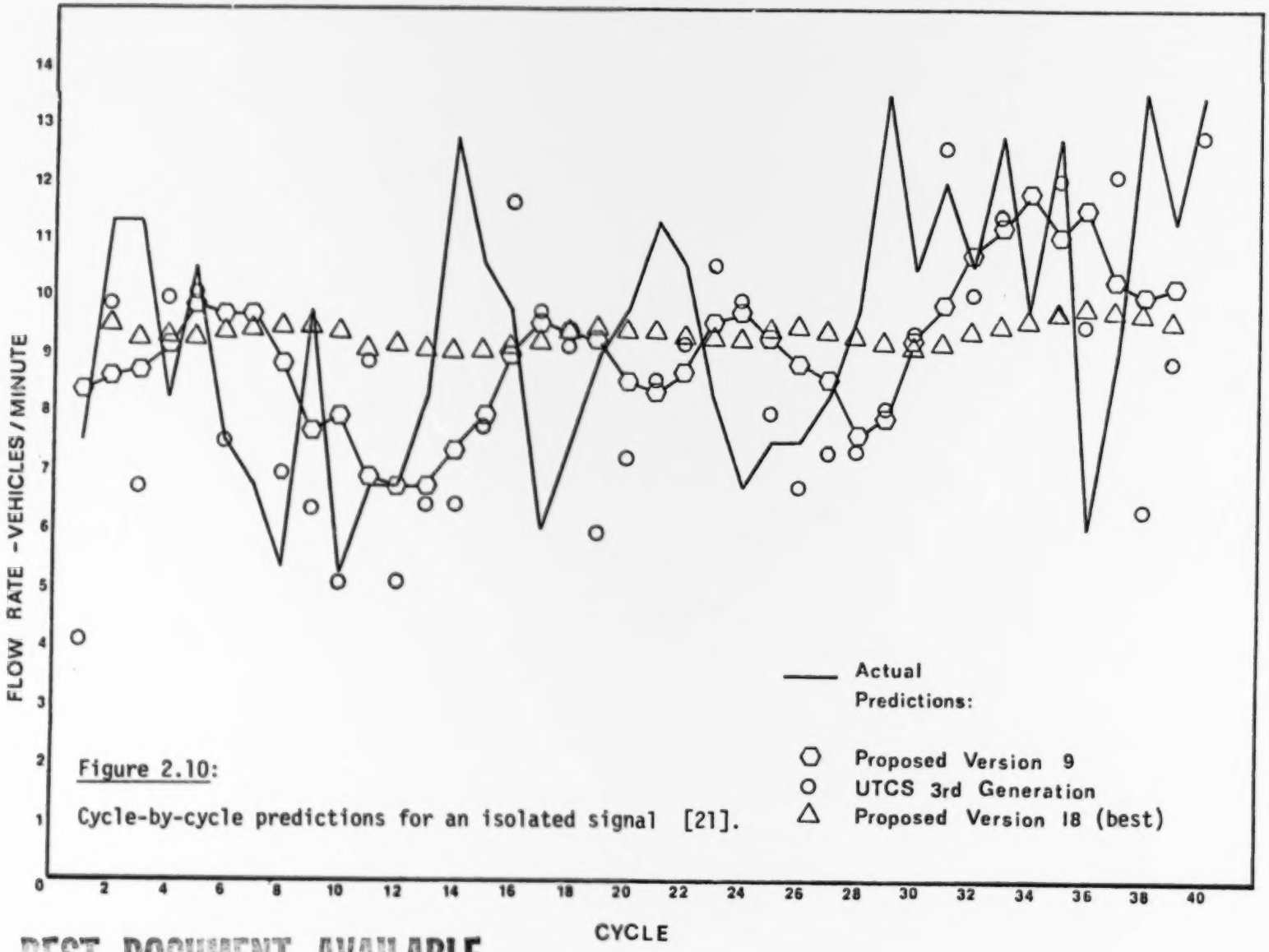

Figure 2.10:

Cycle-by-cycle predictions for an isolated signal [21].

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Table 2.6: Typical Arrival Matrix (in veh/2-sec. interval).

Rows Represent Cycles and Columns Represent Successive Time Intervals.

Cycle No.	Time Interval																														Veh./Cycle	Veh./5-min.
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30		
1	1	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1	1	0	1	1	0	0	0	0	1	1	1	11	
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	2	
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	2	0	1	0	1	1	1	1	0	0	1	1	1	1	12	
4	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	2	0	1	0	1	1	1	1	0	1	0	1	11	
5	0	1	1	1	0	1	1	1	0	0	0	0	1	0	0	1	0	1	0	1	1	0	1	0	1	1	0	1	0	0	15	51
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1	1	1	1	0	1	0	0	1	9	
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	1	0	1	0	0	0	0	1	0	5	
8	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	1	1	1	13	
9	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	1	1	1	0	0	1	1	11	
10	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	1	2	0	1	1	1	12	50
11	1	0	1	0	1	0	1	1	0	0	0	0	0	0	0	0	1	1	1	0	1	1	1	1	1	1	0	1	1	1	17	
12	0	1	1	1	1	0	0	0	0	0	1	0	0	0	0	1	0	2	0	1	1	1	1	1	1	1	0	0	0	0	15	
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1	0	1	1	0	0	6	
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	1	0	1	1	1	1	7	
15	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	1	1	1	0	1	0	10	55

2.5 Conclusions

The more responsive modes of control should be capable to provide results that are better than those produced by the off-line modes. Various simulation studies indicate that if, under ideal conditions, complete information on vehicle arrivals was available, responsive control strategies could reduce as much as 50% of the delay incurred by using existing non-responsive strategies [24,25]. In conclusion, we propose the following requirements for the development of an effective demand-responsive traffic control system:

(1) The system shall provide better performance than off-line methods. This is the primary criterion, everything else is secondary.

(2) Needs development of new concepts and not merely the extension of existing concepts. As demonstrated by the experiments reviewed in this chapter, effective responsiveness is not achieved by just implementing off-line methods at an increased frequency. New methods have to be developed.

(3) Be truly demand-responsive, i.e., adapt to actual traffic conditions and not to historical or predicted values that may be far off from the actual.

(4) Not be arbitrarily restricted to control periods of any length, but can be updated at any time, at any location.

(5) Is not encumbered by a network model structure that requires extensive centralized computer capability, but is decentralized in its decision-making and uses only those data that are directly pertinent to the decisions it has to reach.

(6) Obviates the conventional notions of offset, split, and cycle time, which are inherent in all existing signal optimization methods.

(7) The pattern of any individual signal should consist of a continuously varying, demand-responsive, sequence of ON (effective green) and OFF (effective red) times that are only subjected to appropriate lower and upper bounds.

The following chapters describe the studies conducted toward the development of such a system.

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3. OPTIMIZATION POLICIES FOR ADAPTIVE CONTROL: A DYNAMIC PROGRAMMING APPROACH (OPAC-1)

3.1 Introduction

This chapter describes a method and a computer program (acronymed OPAC-1) that calculates demand-responsive (i.e., which respond to demand in real-time) optimum control policies for an adaptive-signal-controlled intersection. A policy consists of the sequence of signal switching times that minimizes the total delay over the horizon being considered. The horizon can be any period for which flows (arrivals) to the intersection are known or can be predicted; we use a horizon that is several minutes long. Optimization is based on Dynamic Programming which assures global optimality of the performance measure. Since our objective is to obtain the best possible performance, the policies are completely adaptive, depend on arrivals only, and are not subjected to any arbitrary constraints. Consequently, the common notions of cycle time, splits and offsets that characterize traditional signal setting procedures do not apply in this situation.

3.2 Characteristics of Dynamic Programming Problems

Dynamic Programming (DP) is a mathematical technique used for the optimization of multistage decision processes. In this technique, the decisions (or control values) that affect the process are optimized in stages rather than simultaneously. This is done by dividing the original decision/control problem into small subproblems (stages) which can then be handled much more efficiently from a computational standpoint. DP is a systematic procedure for determining the combination of decisions that maximizes overall effectiveness, or minimizes overall disutility.

In contrast to other mathematical programming methods (such as linear programming), there does not exist a standard mathematical formulation of "the" Dynamic Programming problem. Rather, DP is a general type of approach to optimization and control and the particular equations

that are used must be developed to fit each individual problem. A good deal of ingenuity and insight is required to recognize when a problem can be solved by dynamic programming procedures and how it should be done. There are a number of basic features which characterize all DP problems [1]:

1. The problem is divided into stages n, n = 1, ..., N, with a policy decision required at each stage (see Figure 3.1).
2. Each stage is characterized by four factors:
   - an input state I that gives all relevant information about the system at the beginning of the stage; the number of states may be either finite, or infinite
   - an output state O that gives all relevant information about the system at the end of the stage
   - a decision variable x that controls the operation of the stage, and
   - a stage return (performance measure) r, a scalar variable that measures the utility/disutility contributed by the stage, as a single-valued function of inputs and decisions, that is

$$r = R(I,x) \tag{3-1}$$

3. The effect of the policy decision at each stage is to transform the current state into a state associated with the next stage. The stage transformation T, a single-valued transformation, expresses each component of the output state as a function of the input state and decision, that is,

$$O = T(I,x) \tag{3-2}$$

4. Given the current state, an optimal policy for the remaining stages is independent of the policy adopted in previous stages. For DP problems, in general, knowledge of the current stage of the system conveys all the information about its previous behavior necessary for determining the optimal policy henceforth. This property is referred to as the Principle of Optimality,

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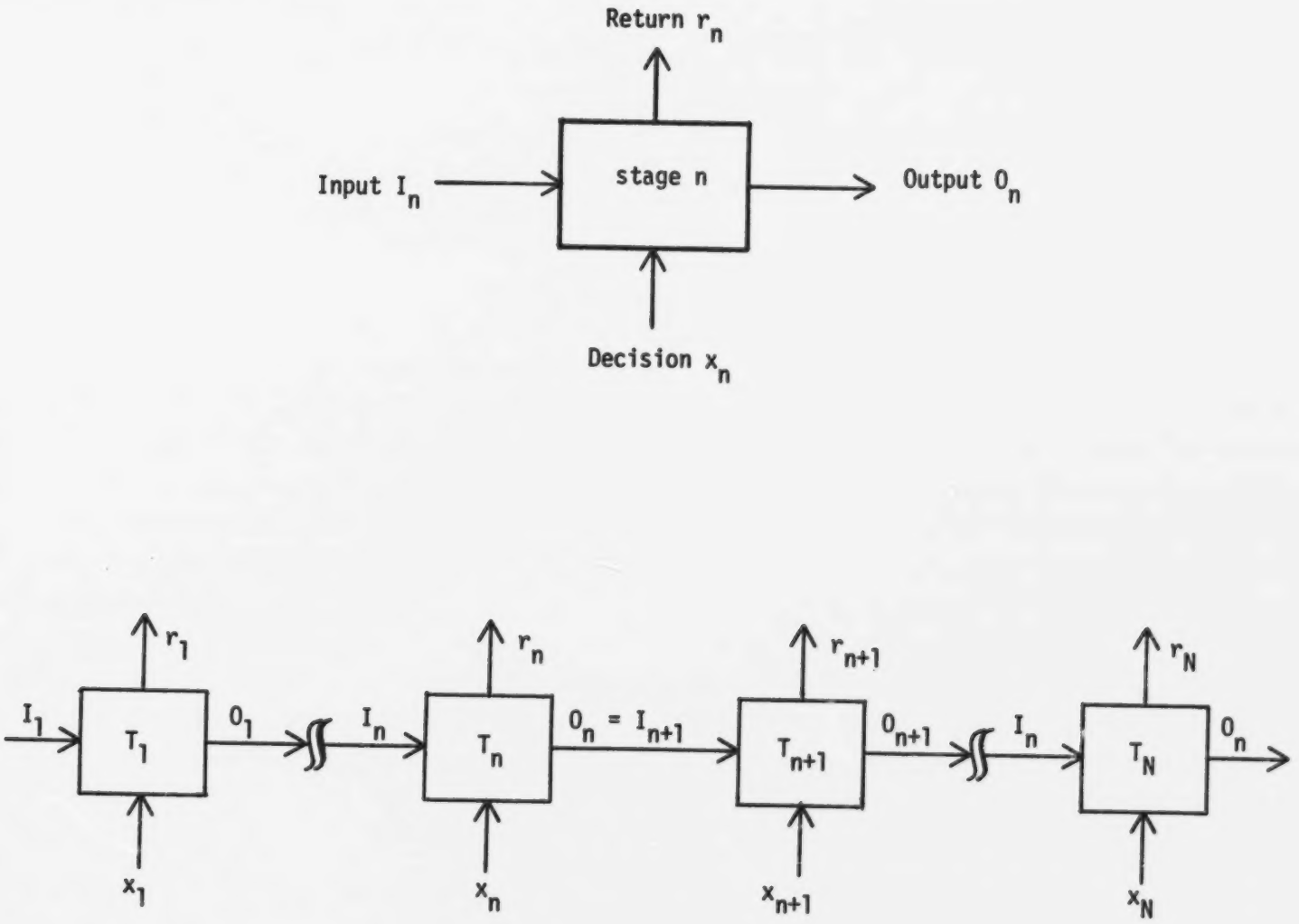

Figure 3.1: Multistage Decision Process

which was enunciated by R.D. Bellman as follows:

> "An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision"[2].

5. A recursive relationship that identifies the optimal policy for each state at stage n, given the optimal policy for each state at stage (n+1). The optimal policy at stage n is the optimizing value of x_n at this stage, given an initial state I_n. This policy consists of using this value of x_n, then following an optimal policy when starting in the state resulting from this decision at stage n+1, and so forth until the final stage N is reached. The objective value at stage n is

$$f_n(I_n,x_n) = R_n(I_n,x_n) + f^*_{n+1}(I_n,x_n) \qquad (3\text{-}3)$$

i.e., $f_n(I_n,x_n)$ calculates the sum total of returns from stage n onwards. Let $f^*_n(I_n)$ be the optimizing value of $f_n(I_n,x_n)$ over all possible values of x_n. The recursive relationship is then

$$f^*_n(I_n) = \underset{x_n}{\text{opt}} \left\{ f_n(I_n,x_n) \right\} = \underset{x_n}{\text{opt}} \left\{ R_n(I_n,x_n) + f^*_{n+1}(I_n,x_n) \right\}. \qquad (3\text{-}4)$$

6. Using this recursive relationship, the solution procedure moves backward stage by stage--each time finding the optimal policy for each state of that stage--until it finds the optimal policy when starting at the initial stage.

For all DP problems, a table (or array) such as the following would be obtained for each stage (n=N,N-1,...,1):

I_n	$f^*_n(I_n)$	x^*_n

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7. When this table (array) is finally obtained for the initial stage (n = 1), the problem is solved. Since the initial state would be known, the initial decision is specified by $x_1^*(I_1)$ in this table. The optimal value of the other decision variables would then be specified by the other tables, according to the state of the system at each stage. The entire optimal policy is thus retraced moving in a forward direction, i.e., going from n = 1 to n = N.

The general computational scheme of DP is illustrated in the flow chart of Figure 3.2. The upper section is the backward moving optimization procedure, whereas the lower part is the forward-tracing of the optimal policy. The dashed boxes and lines indicate the storing of information and its in-flow and out-flow.

3.3 Modeling the Intersection Control Problem

There is a tremendous variety of problems associated with the optimal control of traffic intersections, but only a limited number of special cases have been studied in any detail. The most common approach is to determine settings for a fixed-cycle light which minimize the average delay per car assuming constant arrival rates [3,4]. Gazis and Potts obtained conditions for the optimal control of an intersection which becomes oversaturated for some finite length of time [5]; the model has been extended by Gazis to two intersections [6]. The same modeling approach has also been studied by Michalopoulos and Stephanopoulos [7]. Dunne and Potts developed time-varying control algorithms for an undersaturated intersection with constant arrivals which guarantee that, for any initial state, the system will eventually reach a limit-cycle for which the average equilibrium delay per car is a minimum [8,9]. In all these models, the dynamics of the control policy are not responsive to the dynamics of the traffic flow process since there is no real-time traffic flow information. The traffic flow process is represented by a single value (the expected flow rate), a statistical distribution (Poisson, binomial, etc.), and the initial conditions (the initial queue-lengths); or, in case of oversaturation, by a smooth function

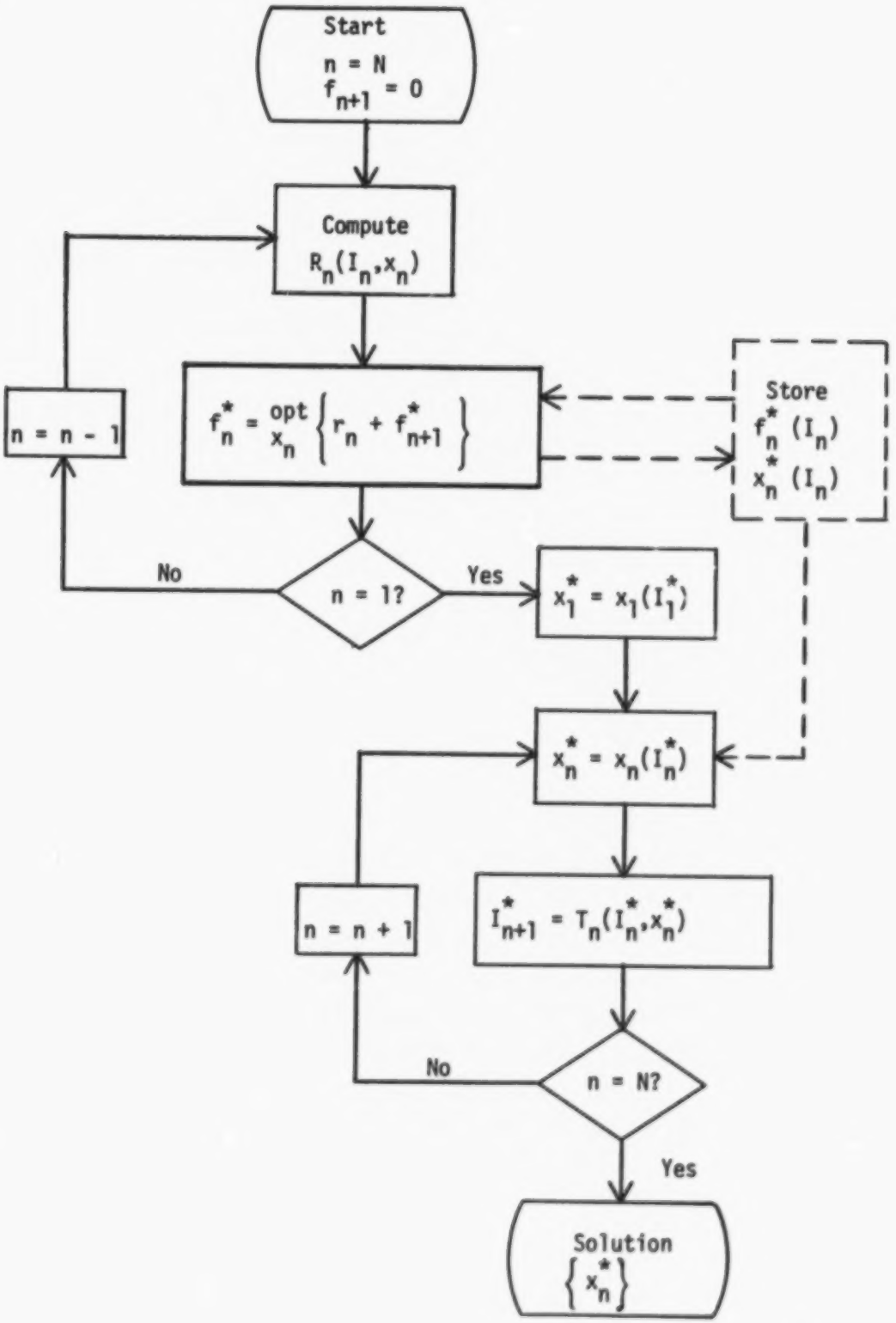

Figure 3.2: General Scheme of Dynamic Programming

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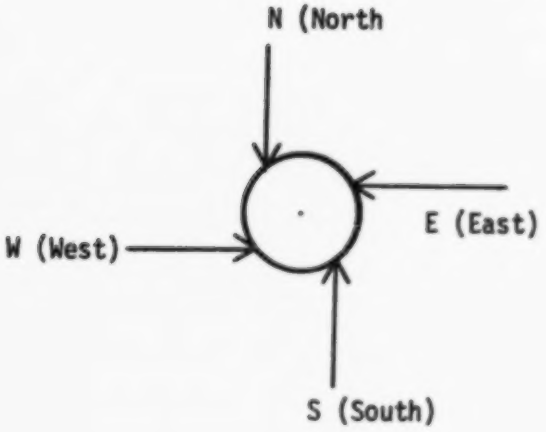
of demand versus time. Obviously, none of these models can take advantage of the time-variant features of individual vehicle arrival times.

A dynamically self-optimizing strategy has been proposed by Miller [10]. In this strategy, a decision whether to extend a phase is repeatedly made at very short fixed intervals h by the examination of a delay-based control function. This function estimates the difference in vehicle-seconds of delay between the gain to the extra vehicles that will be allowed to cross the intersection during an extension of h-seconds and the loss to the queueing vehicles on the cross-street resulting from the extension (h is 1 - 2 seconds long). A similar approach was also proposed by van Zijverden and Kwakernaak [11]. Bang and Nilsson implemented and field-tested Miller's strategy and showed that significant gains can be obtained compared with fixed-time and vehicle-actuated control at isolated intersections [12]. However, since this method has a very short projection horizon and corresponding optimization interval, it does not appear to lend itself to implementation in a network of intersections and, furthermore, does not assure overall optimality of the control strategy. Because of its capability for multistage decision-making, Dynamic Programming is an attractive candidate technique for dynamic optimal signal control. Two DP models have been proposed in the literature for optimal signal control: Grafton and Newell [13] developed a continuous-time model, whereas Robertson and Bretherton [14] used a discrete-time model. The first model chooses to minimize an infinite-horizon total discounted delay function. The second model minimizes the total delay aggregated over all intervals of a finite horizon. Similar to the second model, OPAC-1 is a discrete-time implementation of DP [15].

OPAC-1 is described with reference to the situation illustrated on the next page:

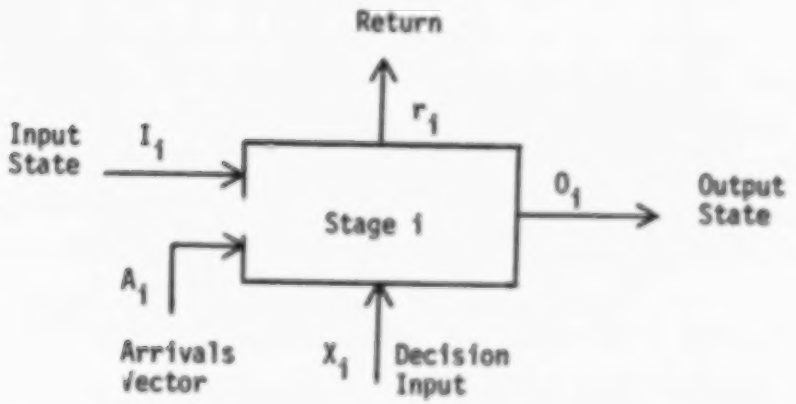


Traffic is arriving on approaches N, S, E and W. The intersection is controlled by a two-phase light providing alternately green to the N-S (phase 1) and E-W (phase 2) approaches. The following assumptions are made:

1. Time is divided into 5-second intervals. All calculations are carried out for the interval as a unit, irrespective of any variations that might occur within the unit. Signals may change only at the boundary between the units.
2. Traffic is assumed to be homogeneous. The arrival rates on the approaches are assumed to be known throughout the horizon and specified by an integer number of vehicles in each interval.
3. Signal phases are composed of effective greens and effective reds only (there is no amber interval). There must always be an overlapping red ("all-red") interval following a decision to switch lights. This period is assumed to include that part of the amber which is effectively red as well as the "lost time" at the start of the green.
4. When the signal is green, the maximum discharge rate on an approach is 2 vehicles per interval. This equals a saturation flow (capacity) of 1440 vehicles per hour of green, which closely corresponds to the capacity of a single traffic lane.
5. No constraints are imposed on the minimum or maximum length of the green periods.

3.4 Optimization Process

The optimization process is decomposed into N stages as shown in the schematic diagram of Figure 3.1. The total number of stages n corresponds to the horizon length of our input predictions. Considering our two-phase signalized intersection, the stages in the process correspond to the discrete time intervals into which the arrival rates are aggregated (therefore, the designation i). A typical stage i is illustrated below:



At stage i we have an input state vector I_i, an arrivals vector A_i, output state vector O_i, input decision variable x_i, economic return (cost) output r_i, and a set of transformations:

$$O_i = T_i(I_i, A_i, x_i) \qquad (3\text{-}5)$$

$$r_i = R_i(I_i, A_i, x_i) \qquad (3\text{-}6)$$

The state of the intersection is characterized by the state of the signal (green or red) and by the queue-length on each of the approaches. The input decision variable indicates whether the signal is to be switched at this stage or remain in its present state. The return cost output is the intersection's index of performance (the total delay time), which has to be minimized. The functional relationships between the input and output variables are based on the queueing-discharge processes occurring at the intersection, i.e., the phenomena of inflow and outflow as a function of the signal settings.

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We define the following variables (all corresponding to stage i):

- a = approach designation, by direction, a = N,S,E,W
- A^a = number of arrivals during interval
- D^a = number of departures (discharges) during interval
- Q^a = the queue-length on the approach at the beginning of the stage
- S^a = status of signal at start of interval
- x = stage input decision variable

The input state vector (transposed) is: $I' = \left[I^N, I^S, I^E, I^W\right]$, where the individual approach state is

$$I^a = \begin{bmatrix} S^a \\ Q^a \end{bmatrix} \tag{3-7}$$

The output state vector contains the same elements as the input state vector and is directly related to the input state of the succeeding stage, i.e.,

$$O_i = I_{i+1} \tag{3-8}$$

The signal status for each approach a, is defined as follows:

$$S^a = \begin{cases} 0 & \text{if green} \\ 1 & \text{if red} \end{cases} \tag{3-9}$$

The input decision variable is

$$x = \begin{cases} 0 & \text{no change} \\ 1 & \text{change} \end{cases} \tag{3-10}$$

The transformation of input to output, at stage i, is as follows:

$$S^a_{i+1} = (S^a_i + x_i)_{\text{mod } 2} \tag{3-11}$$

$$Q^a_{i+1} = Q^a_i + A^a_i - D^a_i \tag{3-12}$$

The mod 2 operation ensures that S^a_{i+1} will always be 0 or 1.

While the arrival rates A^a_i are a given input (not an input state), the departure rate is a function of the state and decision variables:

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$$D = \begin{cases} 0 & \text{if } S = 1 \\ Q + A & \text{if } S = 0 \text{ and } Q + A \leq 2 \\ 2 & \text{if } S = 0 \text{ and } Q + A > 2 \end{cases} \qquad (3\text{-}13)$$

Dynamic programming optimization is carried out in backwards order, i.e., starting from the last time interval and back-tracking to the first, at which time an optimal switching policy for the entire time horizon can be determined. The switching policy consists of the sequence of phase switch-ons and switch-offs throughout the horizon.

The recursive optimization functional is given by equation (3-4), i.e.,

$$f_i^*(I_i) = \min_{x_i} \left\{ R_i(I_i, A_i, x_i) + f_{i+1}^*(I_i, A_i, x_i) \right\} \qquad (3\text{-}14)$$

where the return at stage i is the queueing delay incurred at this stage:

$$r_i = R_i(I_i, A_i, x_i) = \sum_a (Q_i^a + A_i^a - D_i^a) = \sum_a Q_{i+1}^a \qquad (3\text{-}15)$$

$$\text{for } a = N, S, E, W$$

The returns r_i are measured in vehicle-interval units. Thus, when the optimization is complete at stage i = 1 we have

$$f_1^*(I_1) = \min_{x_i} \left\{ \sum_{i=1}^{N} R_i(I_i, A_i, x_i) \right\} = \sum_{i=1}^{N} r_i(I_i, A_i, x_i^*) \qquad (3\text{-}16)$$

which is the minimized total delay over the horizon period for a given input state I_1. Since the initial conditions at stage 1 are specified (i.e., the queue-lengths on all approaches are given as well as the initial signal status), we can retrace the optimal policy by taking a forward pass through the stored tables (arrays) of $X_i^*(I_i)$ (see Figure 3.2). The policy consists of the optimal sequence of switching decisions $\{x_i^*, i = 1, \ldots, N\}$ at all stages of the optimization process.

3.5 Computational Procedure

The computational implementation of the method outlined above is illustrated by two numerical examples, below. At any time interval i,

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the "state" of the intersection is determined by the queue-lengths on its approaches and whether the signal is green in the N-S direction or the E-W direction. The optimum switching policy for subsequent intervals depends only on the current intersection state and on the future arrivals; it is not dependent on any events that occurred during previous intervals. Thus the DP Principle of Optimality can be applied by working backwards from the end of the horizon period towards its beginning.

If at interval i+1 the minimum total delay and optimum switching policy throughout the remainder of the horizon period are known for all possible states at this interval, then this information can be used to calculate the minimum achievable delay and optimum decision at interval i. The procedure consists of simple additions and comparisons and is illustrated in Figure 3.3 and explained below. The same procedure is applied repeatedly, one step at a time, until the first stage has been reached.

For simplicity we consider only two approaches, N and E. Figure 3.3 shows parts of the minimum delay arrays for queues on the two approaches ranging from 0 to 4 vehicles. The left-hand arrays correspond to green on the E-approach, and the right-hand arrays to green on the N-approach. The optimum input decision, x_i, at each stage can be visualized as being stored behind its matching queue and signal state value. The delay calculations at interval i are shown in the rectangular blocks. The procedure of computation is as follows:

Step 1. Select an intersection state at interval i (i.e., the queue-lengths and signal status).

Step 2. Evaluate the total delay for intervals i to n (the last interval in the horizon period) for the following two cases: (i) the signal remains unchanged in its current condition; (ii) the signal is switched, in which case an "all-red" interval follows.

The delay for the two cases can be evaluated from knowledge of the arrivals during interval i, the outflow rates and the

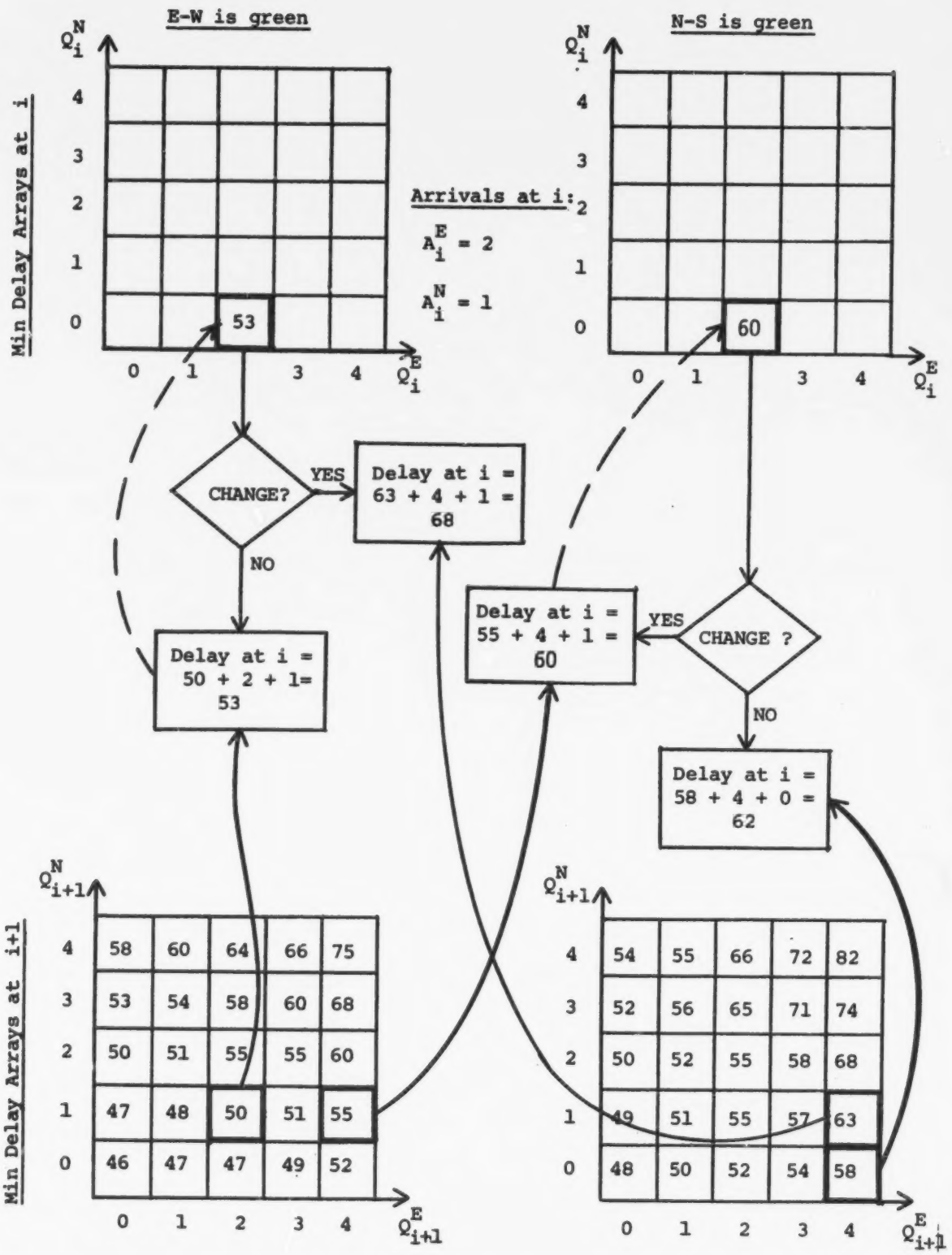

Figure 3.3: Computational procedure of OPAC-1.

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minimum delay associated with the corresponding intersection state at interval i+1 (which was previously calculated).

Step 3. Determine the input decision variable as "change" or "no change", whichever produces less total delay. Register this new minimum total delay in the i-interval array at the intersection state selected in Step 1. Register the input decision value (1 or 0) in the matching decision storage array cell.

Step 4. Repeat Steps 2 and 3 for all states at interval i. The procedure is complete when interval 1 has been reached and yields values for the optimum policy and minimum total delay for each initial intersection state.

Figure 3.3 illustrates two sample calculations. In both cases, arrivals during interval i are: $A_i^E = 2$, $A_i^N = 1$.

EXAMPLE 1.

Step 1: $Q_i^E = 2$, $Q_i^N = 0$, $S_i^E = 0$ (green).

Step 2: If $x_i = 0$ (no change): $Q_{i+1}^E = Q_i^E + A_i^E - 2 = 2$

$Q_{i+1}^N = Q_i^N + A_i^N = 1$

Delay at i = 50 + 2 + 1 = 53

If $x_i = 1$ (change, all red): $Q_{i+1}^E = Q_i^E + A_i^E = 4$

$Q_{i+1}^N = Q_i^N + A_i^N = 1$

Delay at i = 63 + 4 + 1 = 68

Step 3: Choose $x_i = 0$ (no change), Min Delay = 53.

EXAMPLE 2.

Step 1: $Q_i^E = 2$, $Q_i^N = 0$, $S_i^N = 0$ (green).

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Step 2: If $x_i = 0$ (no change): $Q^E_{i+1} = Q^E_i + A^E_i = 4$

$Q^N_{i+1} = Q^N_i + A^N_i - 1 = 0$

Delay at i = 58 + 4 + 0 = 62

If $x_i = 1$ (change, all red): $Q^E_{i+1} = Q^E_i + A^E_i = 4$

$Q^N_{i+1} = Q^N_i + A^N_i = 1$

Delay at i = 55 + 4 + 1 = 60

Step 3: Choose $x_i = 1$ (change), Min Delay = 59.

3.6 OPAC-1 Test Results

Two field-collected traffic flow data sets were used to test OPAC-1 and derive optimal signal control policies. Both sets are for a 2-phase signal, two approaches (designated, for convenience, as Approach A and Approach B), one lane per approach, with a saturation flow of 1440 vph. The arrivals on the approaches, the optimal switching policies and the resulting queue-length histories are illustrated in Figures 3.4 and 3.5. The signal timings are shown as hatched (red) and blank (green) areas. The data sets are:

DATA SET NO. 1: 5-minute period, coordinated signal (Toronto traffic control system), see Figure 3.4A.

DATA SET NO. 2: 8-minute period, isolated signal (Miami traffic control system), see Figure 3.5A.

Two cases have been plotted for each data set: (A) zero initial queues, and (B) 5-vehicle initial queues, on each approach. OPAC-1 calculates policies for up to 20 vehicles in each queue, i.e., we can derive optimal switching policies for any combination of 20 x 20 initial queue states, all from one computer run. The initial signal status is "A is green" (OPAC-1 also provides all 20 x 20 combinations for the initial state "B is green"). We see that the strategies are completely responsive, i.e., determined only by arrivals, and the common notions of cycle, split or offset cannot be used.

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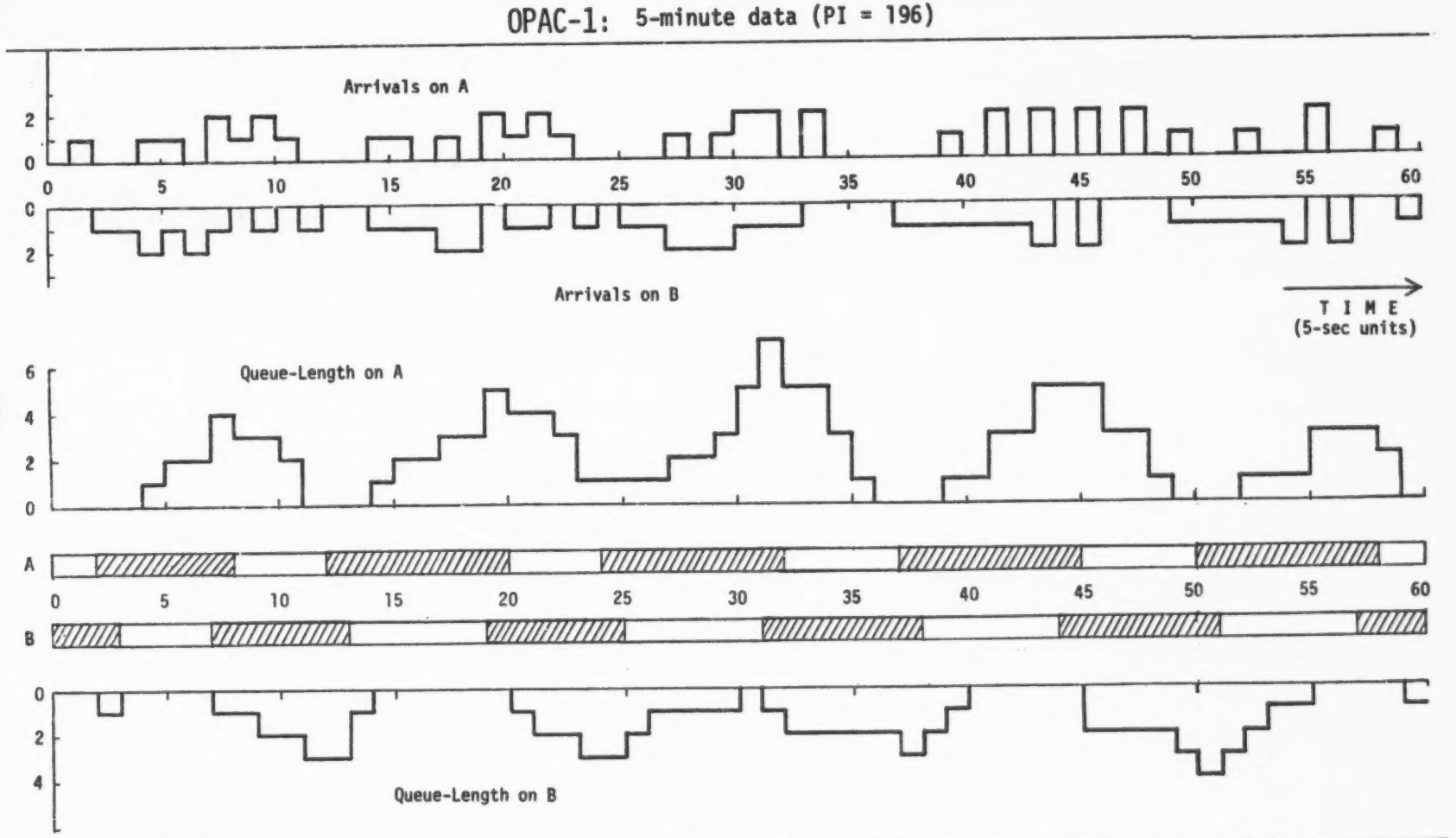

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FIGURE 3.4A

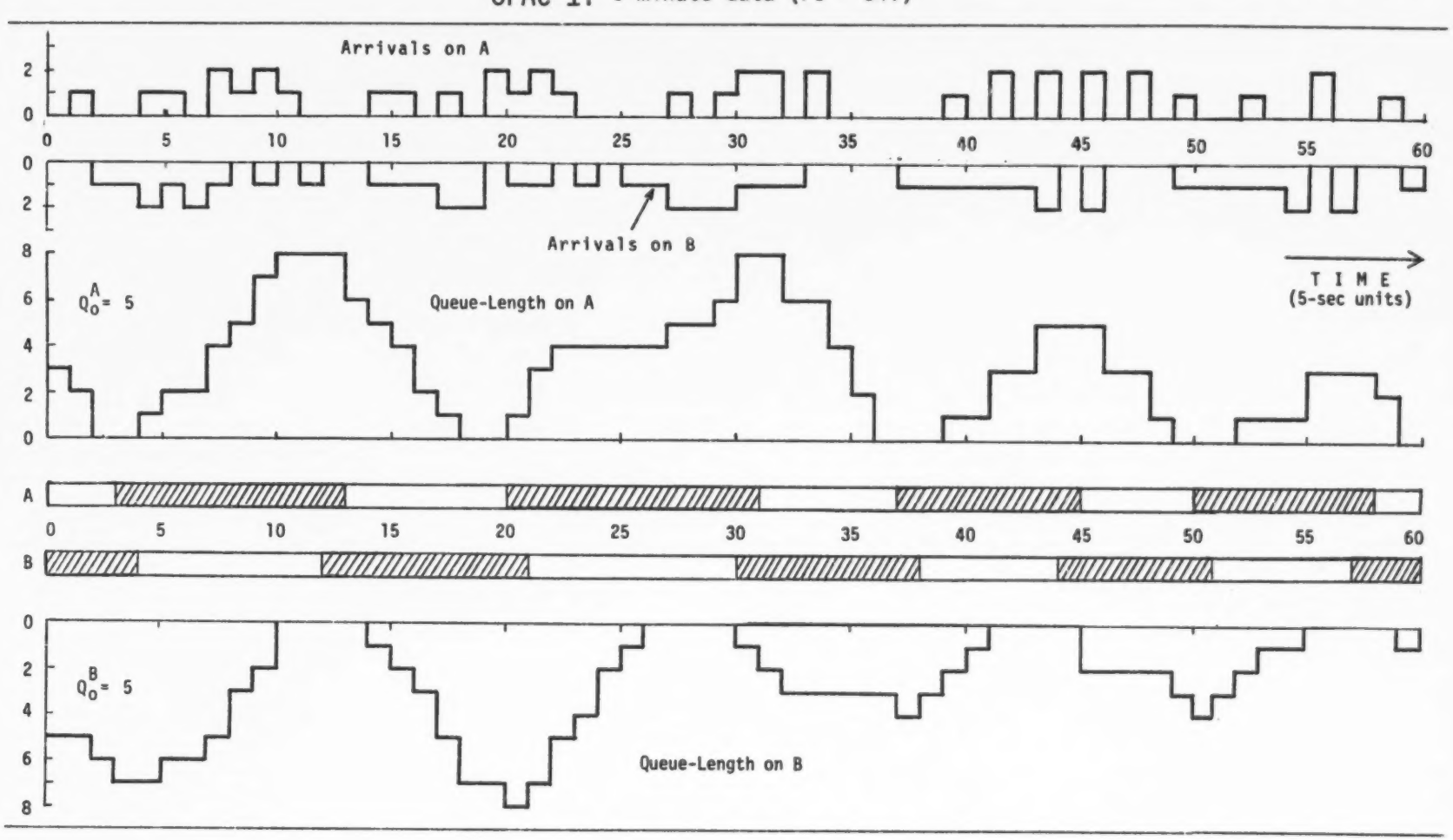

FIGURE 3.4B

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OPAC-1: 8-minute data (PI=148)

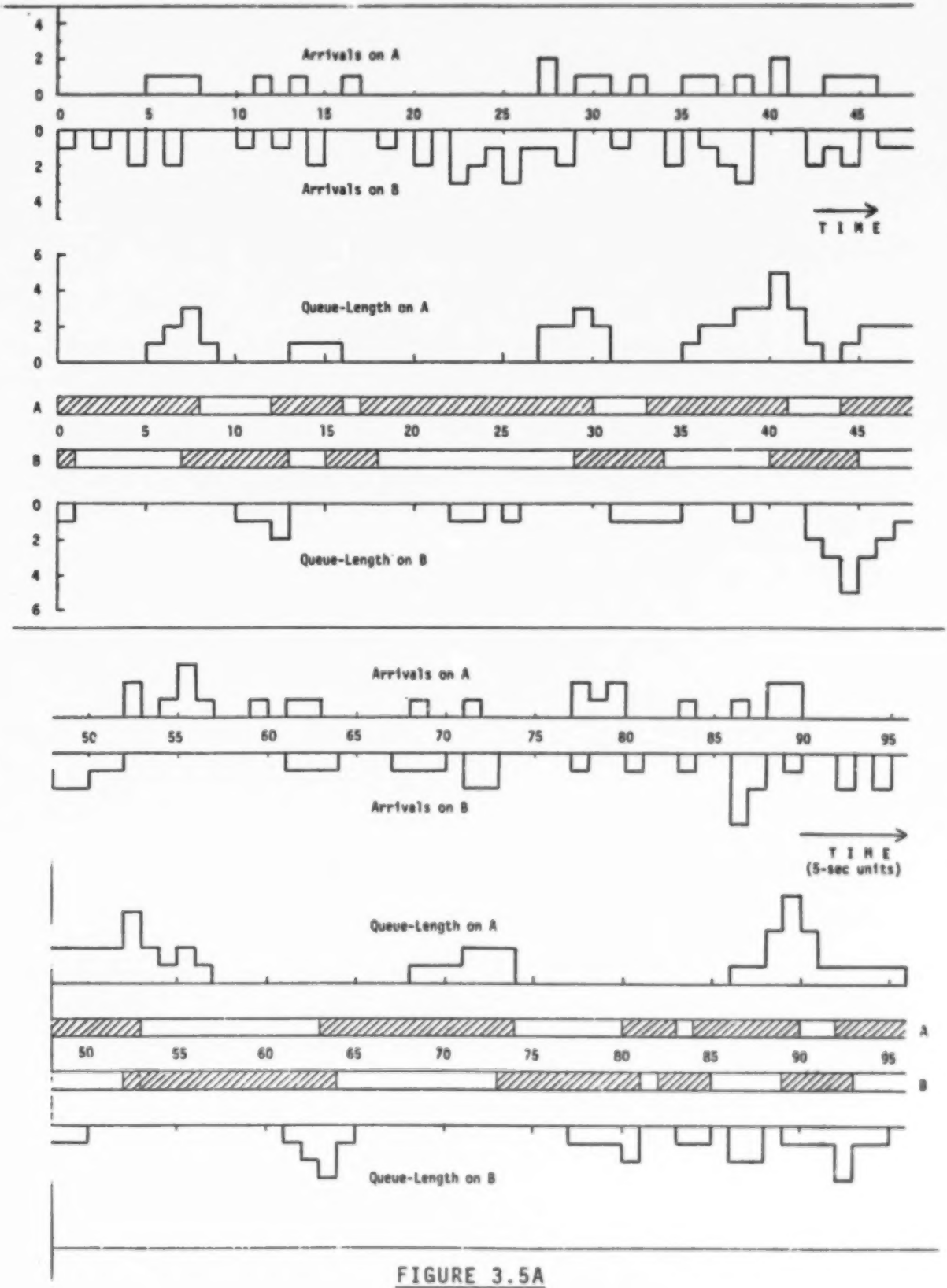

FIGURE 3.5A

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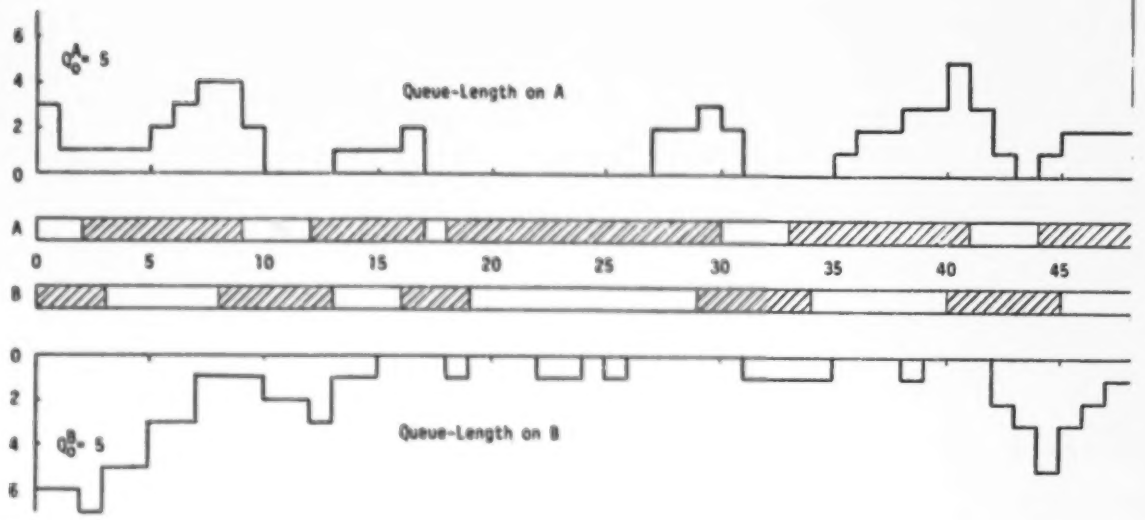
OPAC-1: 8-minute data (PI=208)



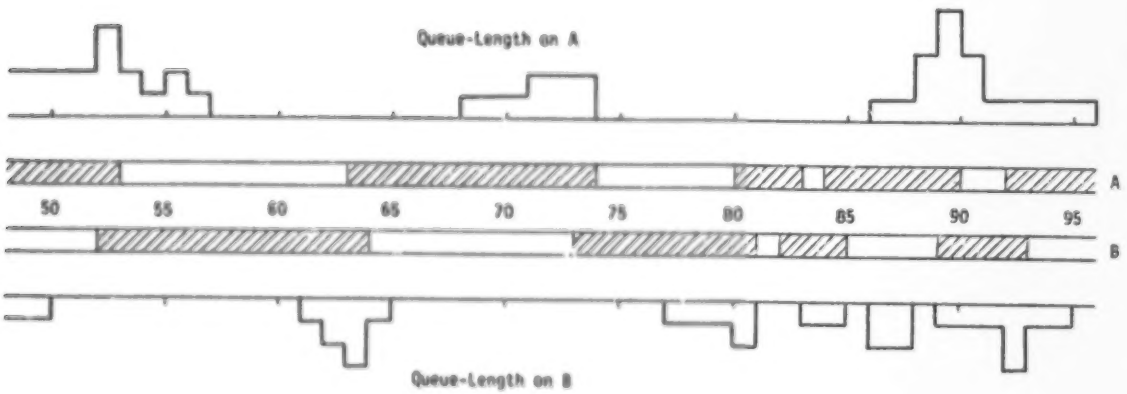


FIGURE 3.5B

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An analysis of the results shown in Figures 3.4 and 3.5 is presented in Table 3.1. All data pertain to the intersection as a unit (as compared to the individual approach as the unit), because of the responsiveness of the strategies involved. The capacity (of the intersection) is calculated as follows:

Capacity (vph) = (1440 vph) x (effective greentime/period),

and depends on the frequency of signal switchings. The average cycle length is calculated as the average time elapsed between two signal switchings, i.e.,

$$\text{Average Cycle Length (sec)} = \frac{\text{Period (min)} \times 60}{\text{No. of Switches}} \times 2$$

The lost time calculation is based on the 5-sec all-red intervals we have at each signal switching point. The performance index (PI) measures the total vehicle-intervals (in 5-sec units) and is the sum of all areas under the queue-length curves. It is an output of the program. The resulting timing policies are optimal in the sense that no other policy can produce a lower PI value for the given initial conditions, this optimality being guaranteed by the Dynamic Programming procedure. The final performance measure, the average delay per vehicle, is calculated as follows:

$$\text{Average Delay Per Vehicle (sec)} = \frac{\text{PI} \times 5\text{(sec)}}{\text{Total No. of Arrivals}}$$

The results obtained with the OPAC-1 policies are compared with Webster-Method-derived settings and measures-of-performance for the same data (Table 3.1, bottom). We observe that, in general, the demand-responsive settings cause only about 1/3 the average delay that would be caused by an optimal fixed-time strategy. Obviously, one has to bear in mind that the DP-derived policies assume full knowledge of arrivals several minutes into the future, which is unlikely to be available in practice. Therefore, these policies should be regarded as ideal policies which set a standard of performance for traffic signal operation. Also, the computation time is relatively long compared to the data time: about 10 CPU-seconds per 1 minute of traffic data, using a CDC Cyber-70 facility (computation time is proportional to data time).

In the next two chapters we describe the development of more practical methods for deriving demand-responsive strategies. These methods have as their goal to come as close as possible to the standards set by OPAC-1 and yet to use only limited flow information and be much more economical in computational requirements.

Table 3.1: Analysis of OPAC-1 Policies

RESULTS	5-Min Data		8-Min Data	
	$Q_o = 0$ (Fig. 3.4A)	$Q_o = 5$ (Fig. 3.4B)	$Q_o = 0$ (Fig. 3.5A)	$Q_o = 5$ (Fig. 3.5B)
Total No. of Arrivals	91	101	114	124
Combined Volume (vph)	1092	1212	855	930
Flow/Sat'n Flow Volume/Capacity	0.76 0.91	0.81 0.97	0.59 0.72	0.65 0.78
Flow Ratio on Approaches	$\frac{40}{51} = 0.78$	$\frac{45}{56} = 0.80$	$\frac{42}{72} = 0.58$	$\frac{47}{77} = 0.61$
Greentime Ratio on Approaches	$\frac{22}{28} = 0.79$	$\frac{23}{29} = 0.79$	$\frac{30}{49} = 0.61$	$\frac{31}{48} = 0.65$
No. of Switches Lost Time (%)	10 16.7	8 13.3	17 17.7	17 17.7
Average Cycle Length (sec)	60	75	56.5	56.5
Performance Index (veh-int'ls)	196	341	148	208
Average Delay (sec/veh)	10.8	16.9	6.5	8.4
Webster Method:				
Cycle (sec)	82.7	126.6	49.3	56.5
Avg. Delay (sec)	33.7	49.9	18.9	23.2
Volume/Capacity	0.86	0.91	0.75	0.78

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3.7 References

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4. OPTIMIZATION POLICIES FOR ADAPTIVE CONTROL: A SIMPLIFIED APPROACH (OPAC-2)

4.1 Introduction

In the previous chapter we described a Dynamic Programming based method for deriving demand-responsive optimal control policies. While assuring global optimality of the results, the extent of the input data it uses and the extensive computational requirements preclude its use as an on-line optimization strategy. We noted, however, that OPAC-1 generates a good deal of information that is never used: we obtain optimal policies for all possible initial conditions, yet we need only one of those policies. The running time and storage space required for calculating all those policies are, in fact, not utilized effectively. Following these observations we develop an optimization procedure that is much simplified. It does not assure global optimality, yet it provides results that are very close to the global. We now can assess the quality of the resulting policies by comparing it with OPAC-1.

4.2 Optimization Procedure

In this section we describe the development of OPAC-2, a simplified method for calculating optimal policies for adaptive signal control. OPAC-2 has the following basic features:

1. The optimization process is divided into stages that are T-seconds long. The process can be infinitely long, in which case we will have a continuous succession of T-long stages.
2. Each stage is divided into an integral number of Δ-sec steps (intervals); i.e., $T/\Delta = k$ (integer). We use $\Delta = 5$ sec (as in OPAC-1), and $k = 10 \div 20$. Therefore, the stage length T will, usually, be in the 50 - 100 seconds range which is similar to the range of cycle times for a fixed-time signal, although there is no correlation between the two.

3. During each stage we require at least one signal change (switchover) and allow up to three switchovers. This is designed to provide sufficient flexibility for deriving an optimal demand-responsive policy. The possible switching sequences are illustrated in Figure 4.1. The switching times (t_1, t_2, t_3) are measured from the start of the stage in 5-sec time units.

4. For any given switching sequence at stage n we define a performance function on each approach that calculates the total delay during the stage (in vehicle-intervals):

$$\phi_n(t_1, t_2, t_3) = \sum_{i=1}^{k} \left[Q_o + A_i - D_i \right]$$

where, Q_o = initial queue
A_i = arrivals during interval i
D_i = departures during interval i

An illustration of the calculation of ϕ for a stage with one switchover is shown in Figure 4.2. ϕ measures the area enclosed between the cumulative arrivals and cumulative departures curves [1].

5. The single-stage optimization problem can now be formulated as follows: ("a" denotes the approach)

Given: Q_o^a, A_i (for i = 1, . . ., k)

Determine: t_1, t_2, t_3

To: $\text{Min} \sum_a \phi_n^a (t_1, t_2, t_3)$

Subject to:

lower bound		decision variable		upper bound
$\underline{t_1}$	$\leqslant$	t_1	$\leqslant$	$\overline{t_1}$
$\underline{t_2}$	$\leqslant$	t_2	$\leqslant$	$\overline{t_2}$
$\underline{t_3}$	$\leqslant$	t_3	$\leqslant$	$\overline{t_3}$

The bounds on the decision variables are determined so that minimum and maximum requirements on phase lengths are maintained, i.e.,

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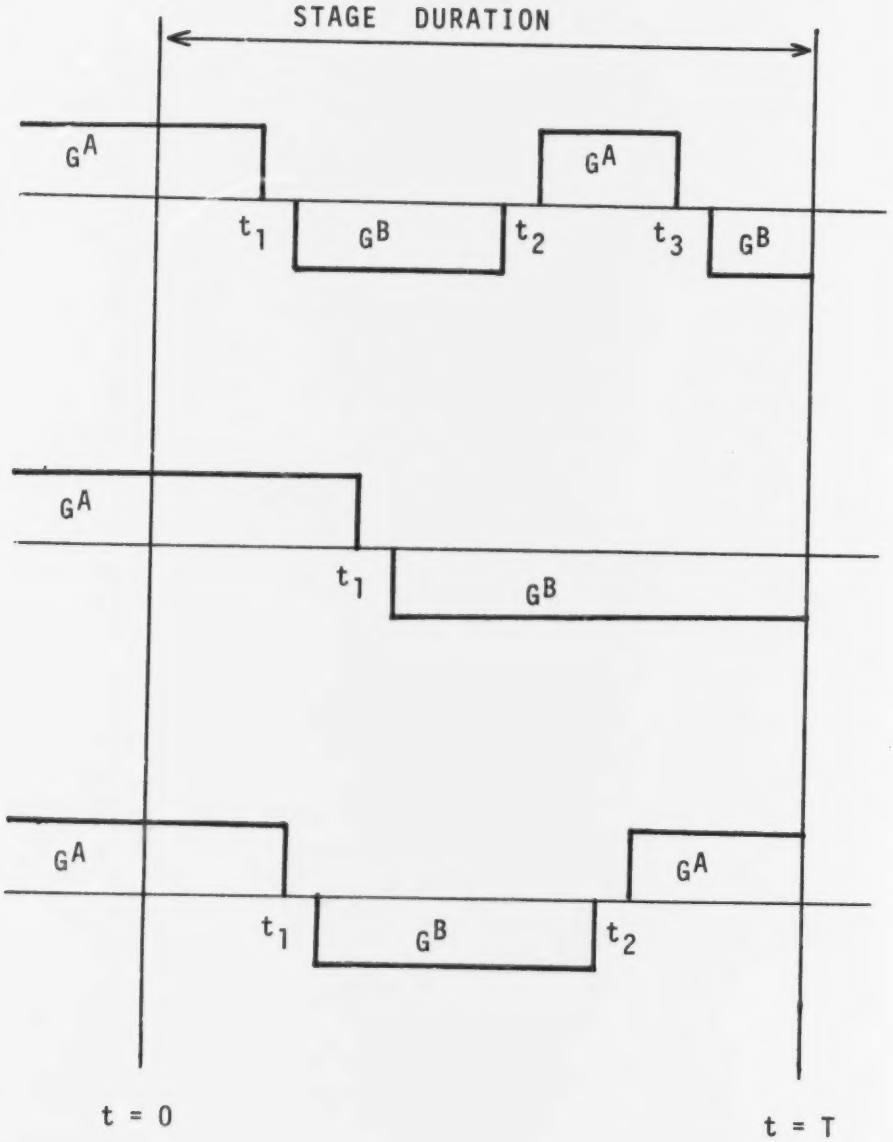

Figure 4.1: Possible switching sequences during one stage. (With green-on-A initial condition.)

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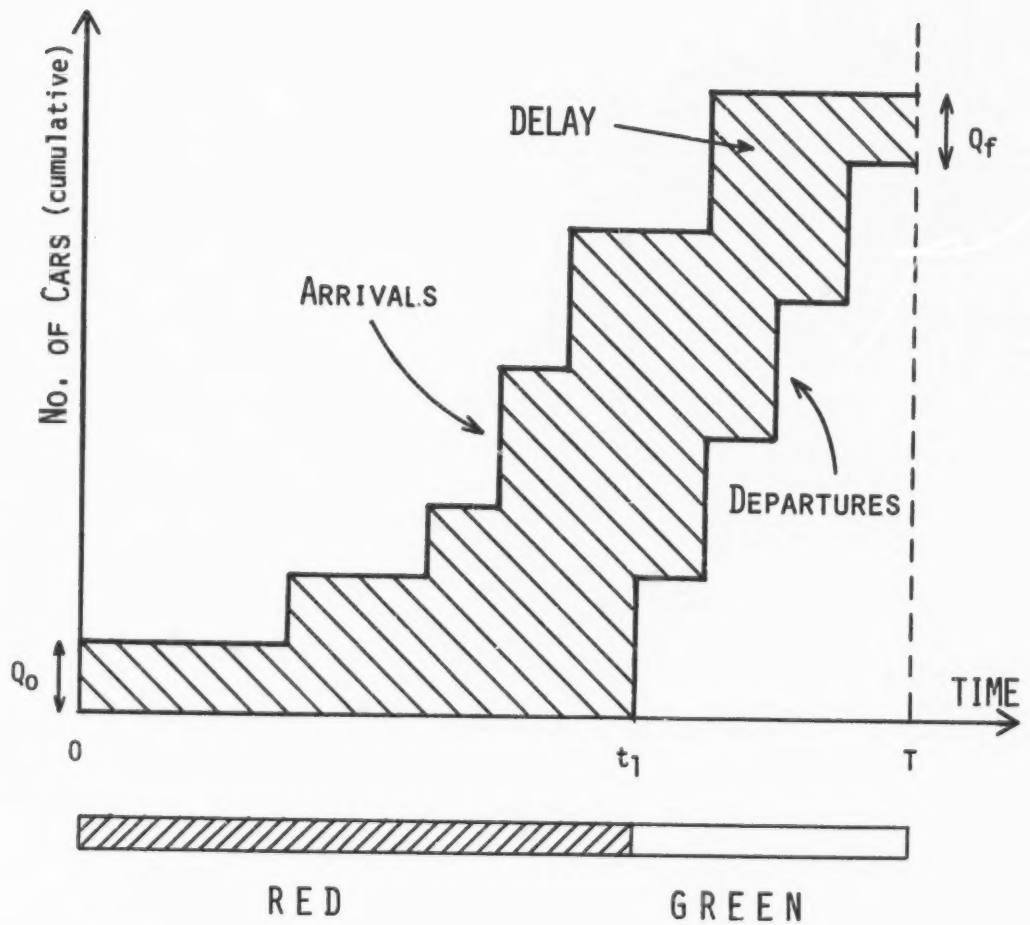

Figure 4.2: Arrivals and departures during one stage.

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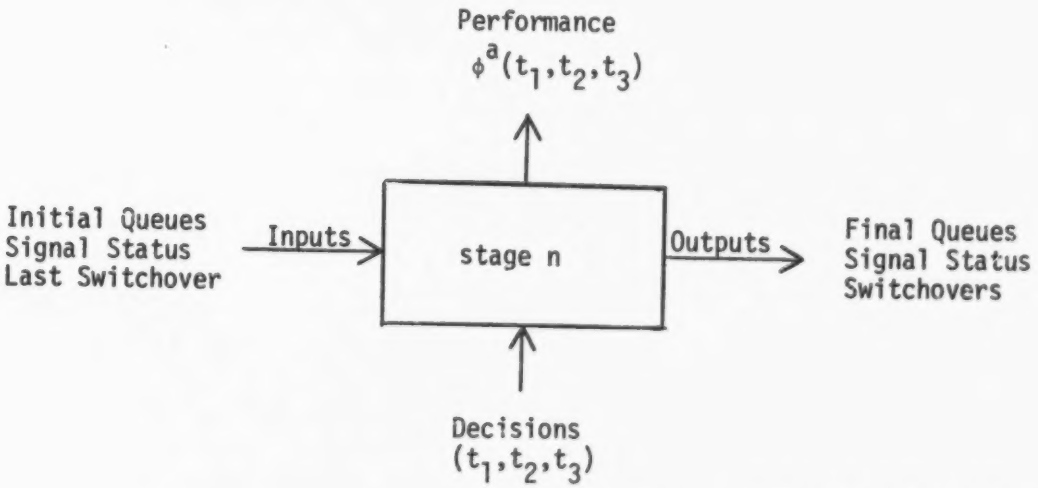
$$\text{minimum phase length} \leq \left(t_{j+1} - t_j\right) \leq \text{maximum phase length}$$

where t_j denotes any switching point (note that we need also to take into account the last switchover in the preceding stage).

6. The optimization procedure used for solving the problem formulated in (5) is an optimal sequential constrained search (OSCO) method [2]. The method is illustrated, in a somewhat simplified manner, by the flow diagram of Figure 4.3. The objective function is evaluated sequentially for all feasible switching sequences. At each iteration, the current performance index (objective value) is compared with the previously stored value and, if lower, replaces it. The corresponding switching point times and final queue-lengths are also stored. At the end of the search, the values in storage are the optimal solution. In case of a tie between two solutions, the one resulting in smaller final queues is chosen.
7. The optimal switching policies are calculated independently for each stage, in a forward sequential manner for the entire process (i.e., one stage after another). Therefore, this approach is amenable for incorporation in an on-line system (unlike the DP approach). The information and decision flow at a typical stage n is illustrated below:



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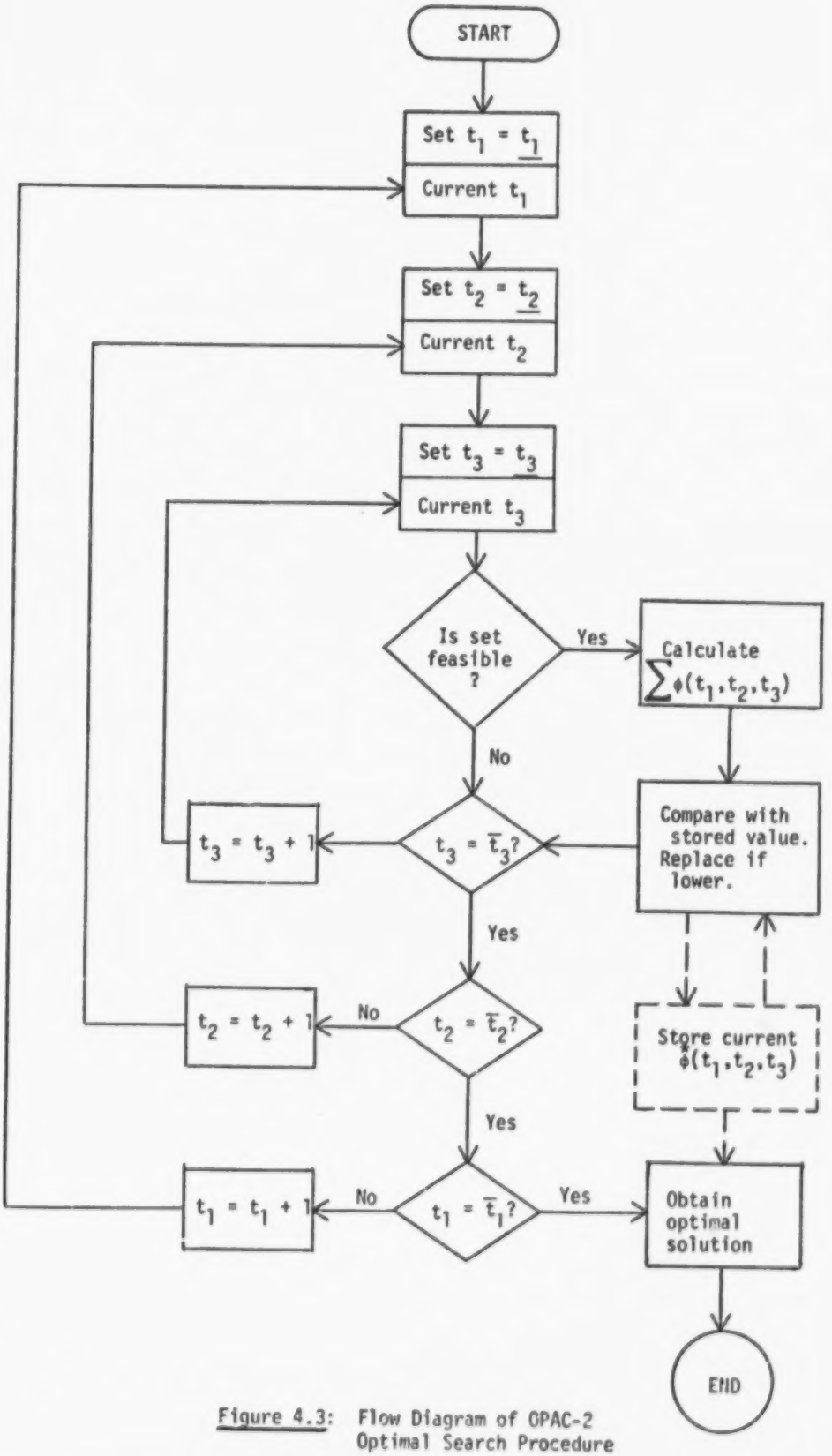

Figure 4.3: Flow Diagram of OPAC-2 Optimal Search Procedure

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4.3 Computational Experience

We used the same two data sets described in Section 3.5 for testing OPAC-2. Figure 4.4A shows the switching policies and queue-lengths obtained for the 5-minute data with: zero initial queues, stage size k = 12 steps, T = 60 seconds. The resulting overall performance index is PI = 203 vehicle-intervals. This compares with the DP calculated optimum of 196 veh-int--a 3.6% deviation.

An inspection of the queue-length curves reveals that OPAC-2 tends to leave longer queues at the end of stages than would OPAC-1 at the same point. This is a natural outcome of this method, since the sequential optimization procedure has a myopic view and, therefore, would like to transfer customers to succeeding stages. To remedy this situation we add to the optimization objective a penalty function which is composed of the weighted sum of final queues Q_f^a on each approach a. The α factor is higher for queues-on-red than for queues-on-green. The penalty function is:

$$P_n(Q_f^a) = \sum_a \alpha^a Q_f^a$$

The addition of this function represents an equivalent delay to the optimization objective and tends to adjust the switching policies (t_1, t_2, t_3) so that the final queues are minimized and, consequently, that only minimal delays are transferred to the succeeding stage. After the introduction of the penalty function we obtained the switching policy shown in Figure 4.4A which is identical to the optimal. The improvement was achieved by the suppression of the queue-on-red at the end of stage four. In other words, the delay in stage four was increased to facilitate a larger reduction in delay in stage 5. All subsequent runs use the penalty function.

Additional runs are illustrated for the 5-minute data in Figs. 4.4B and 4.5 (10-step and 15-step stages), and for the 8-minute data

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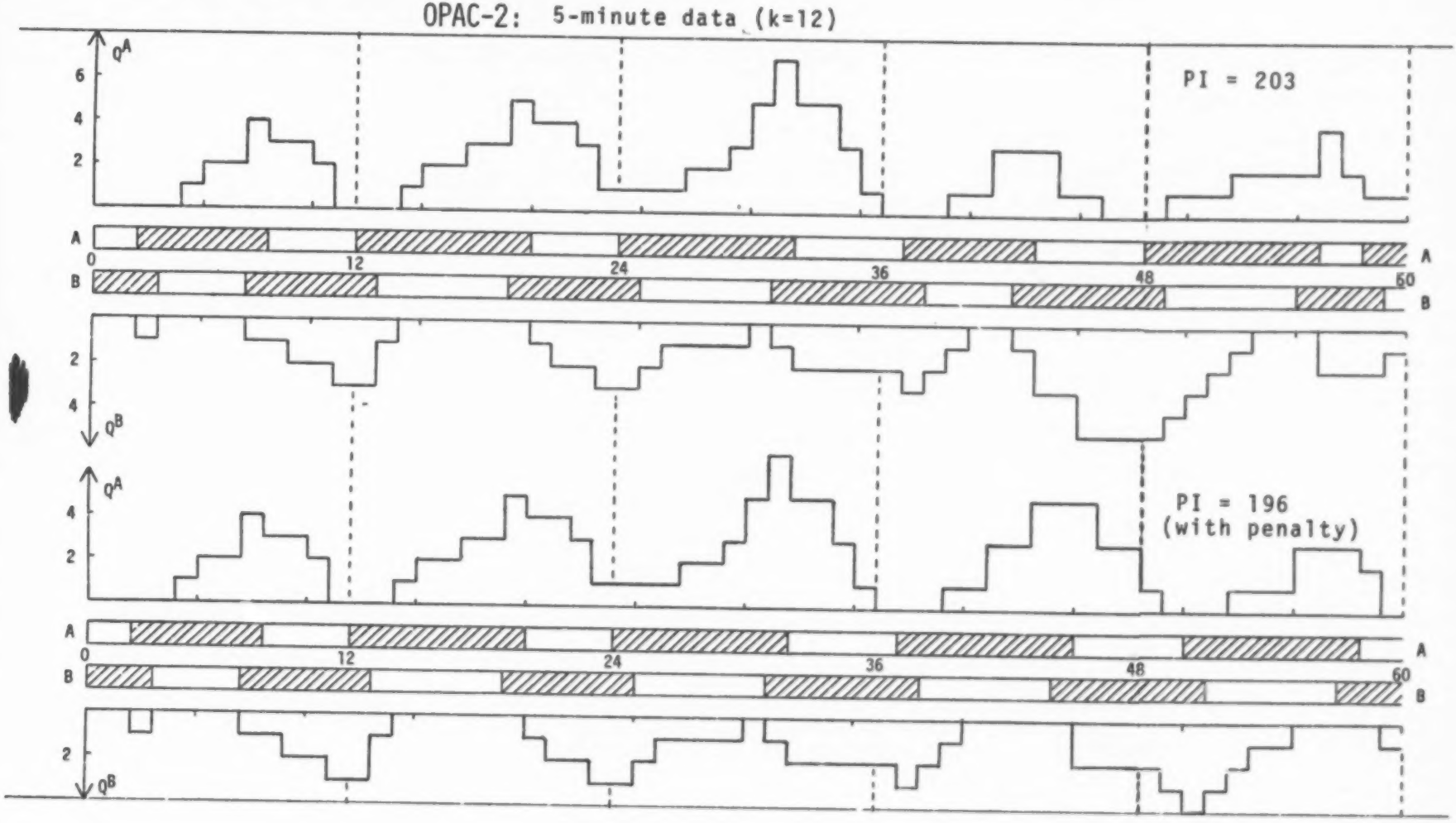

FIGURE 4.4A

OPAC-2: 5-minute data, Q_o = 5 (k = 12)

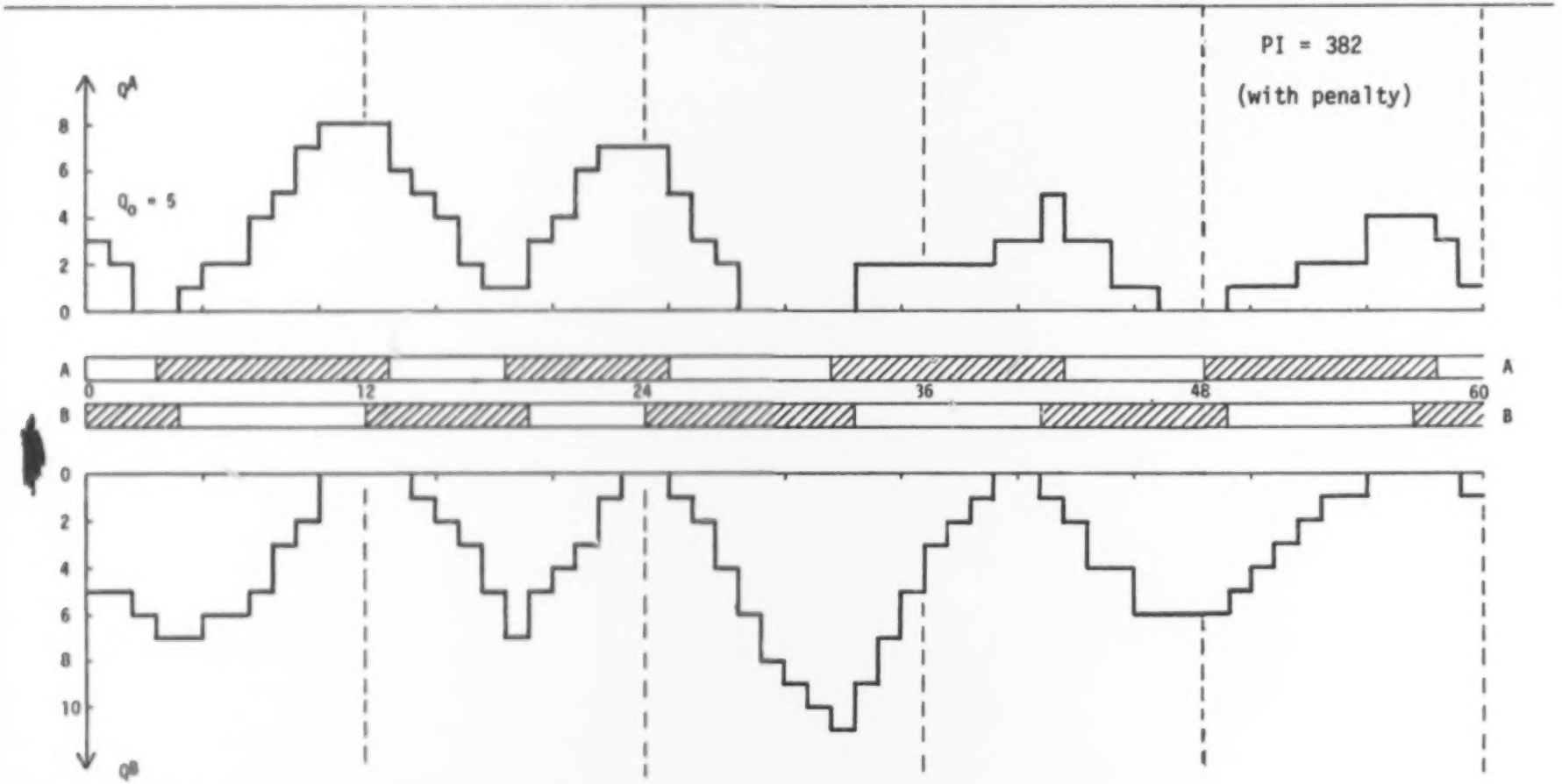

Figure 4.4B

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OPAC-2: 5-minute data (k = 10, PI = 240; k = 15, $\overline{PI}$ = 211)

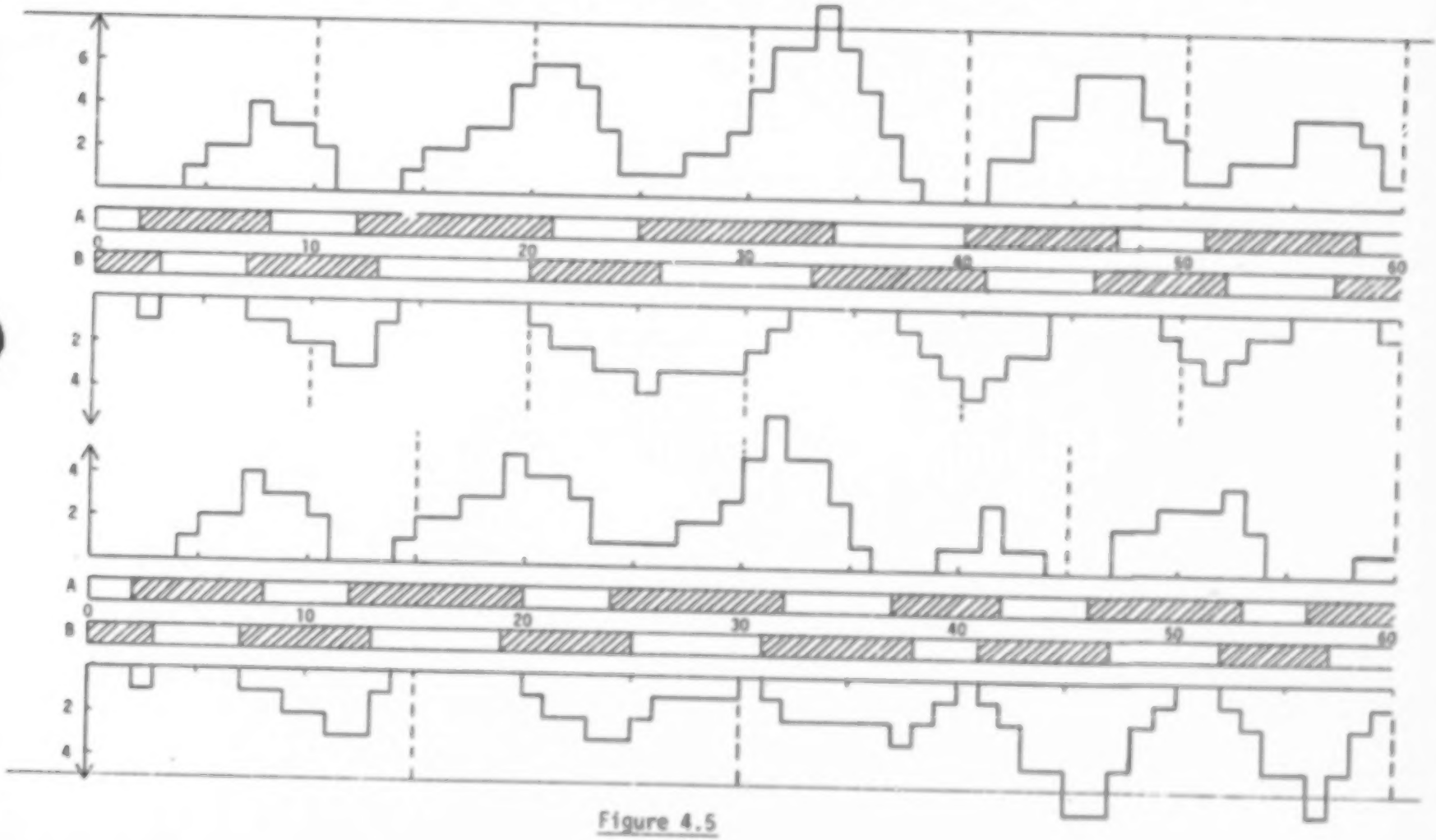

Figure 4.5

in Figure 4.6 (12-step stages) and Figure 4.6B (12-step stage, Q_o = 5). The different runs for the two data sets are summarized in Table 4.1. We see that the results are very close to the optimal, in most cases the difference in PI is under 10%. This is very encouraging, since the horizon used by OPAC-2 has been reduced by a factor of between 1:5 and 1:10. Moreover, running times have also been reduced by a factor of almost 1:10 (1.3 CPU-seconds per minute of traffic data, compared to 10 CPU-sec in OPAC-1).

Thus, the OPAC-2 strategy is much more amenable to demand-responsive decentralized control. However, we still face two problems: (1) the availability of flow data for the reduced horizon (the stage length), and (2) the nonoptimality of the results. We attempt to solve these problems by introducing the rolling horizon concept which is described in the next chapter.

4.4 References

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OPAC-2: 8-minuta data (k=12, PI=159)

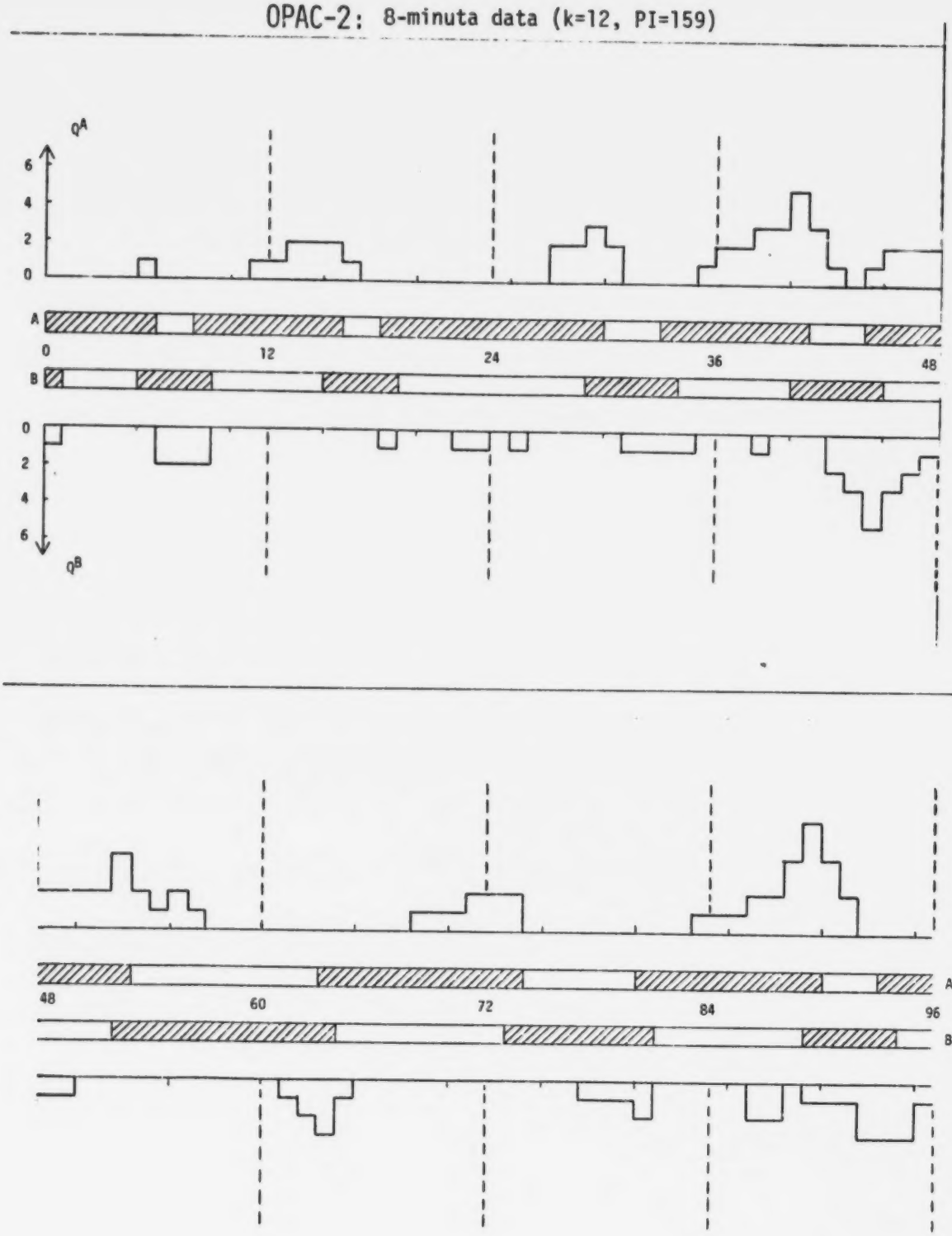

FIGURE 4.6A

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OPAC-2: 8-minute data (k=12, PI=216)

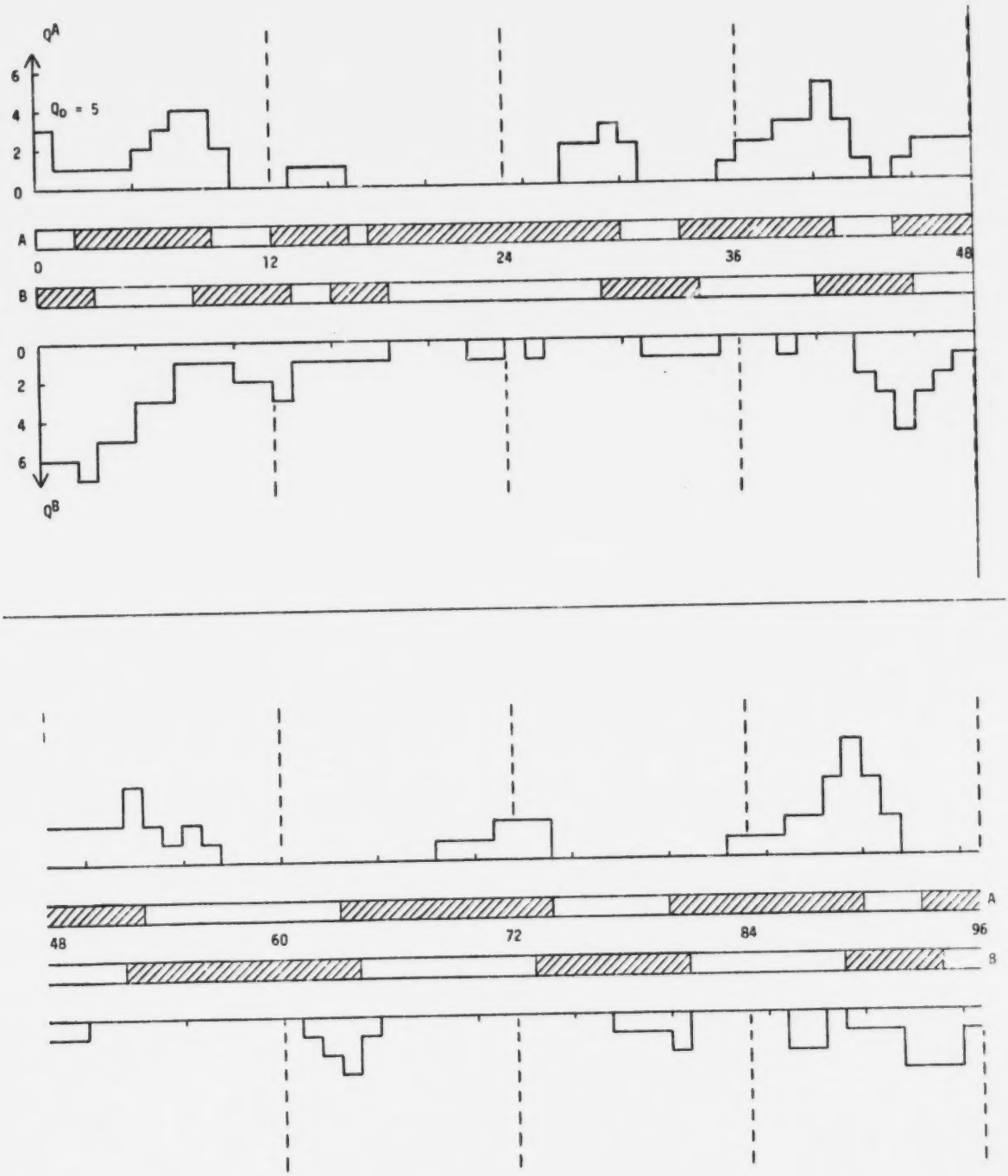

FIGURE 4.6B

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Table 4.1: OPAC-2 Results - Variable Stage Size

5-Min. Data

Stage Size, k	$Q_o = 0$ Performance Index	$Q_o = 0$ Diff. from Optimum (%)	$Q_o = 5$ Performance Index	$Q_o = 5$ Diff. from Optimum (%)
OPAC-1	196	Optimum	341	Optimum
10	240	22.45	356	4.40
12	196	0.0	382	12.02
14	196	0.0	377	10.56
15	211	7.65		
16	201	2.55	356	4.40

8-Min. Data

Stage Size, k	$Q_o = 0$ Performance Index	$Q_o = 0$ Diff. from Optimum (%)	$Q_o = 5$ Performance Index	$Q_o = 5$ Diff. from Optimum (%)
OPAC-1	148	Optimum	208	Optimum
10	151	2.02	211	1.44
12	159	7.43	216	3.85
14	165	11.49	227	9.13
16	159	7.43	215	3.37

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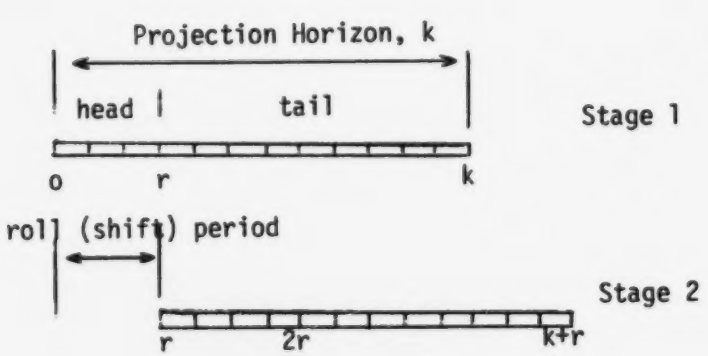
5. OPTIMIZATION POLICIES FOR ADAPTIVE CONTROL: THE ROLLING HORIZON APPROACH (ROPAC)

5.1 Introduction

Chapter 4 identified a basic building block for demand-responsive decentralized control, a simplified optimization technique for determining optimal switching policies in a time-stage of T seconds. The technique requires future arrival information for the entire stage which is difficult to obtain in practice with reliability. To reduce these requirements in such a way that we can utilize only available flow data, yet to preserve the performance of the computational procedure, we introduce the rolling horizon (or rolling schedule) concept [1]. This concept is used by operations research analysts in production-inventory control. The typical situation is as follows: Customer demands are projected for, say, four months (January-April). Based on these projections an optimal production schedule is prepared for the entire period, but is implemented only for the January production control. At the end of the month, when updated demand information is available for the upcoming period, the cycle is repeated: an optimal production schedule is prepared for February-May, February's production plan is implemented; and so on. We apply the same concept to the traffic control problem.

5.2 Rolling Horizon Control Policies

Using the terminology of Chapter 4, the rolling horizon concept is applied to the demand-responsive traffic control problem as illustrated below:



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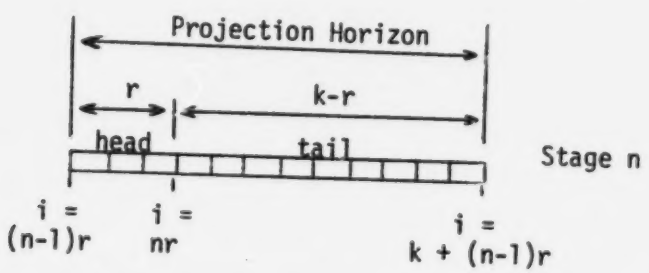
The stage length consists of k intervals (T = Δk seconds), which is the Projection Horizon - the period for which we need traffic flow information. From upstream detectors we can obtain actual arrival data for a near term period of r intervals (the length of which is R = Δr seconds) at the head of the stage. For the next k-r intervals, the tail of the stage, we obtain flow data from a model. We calculate an optimal policy for the entire stage, but implement it only for the head section of R seconds. We then shift (roll) the Projection Horizon r-units ahead, obtain new flow data for the stage (head and tail), and repeat the process. At stage n we have the following situation:



The logic of the optimization process is described by the flow diagram in Figure 5.1 (the computer program is named ROPAC - Rolling Horizon OPAC). The basic steps in the process are described below:

ROPAC Procedure

0. Determine stage length k and roll period r.
1. Obtain flow data for first r intervals (head) from detectors and calculate flow data for next k-r intervals (tail) from model and detectors.
2. Calculate optimal switching policy for entire stage by OSCO (Section 4.2).
3. Implement switching policy for roll period (head) only.
4. Shift Projection Horizon by r units to obtain new stage. Repeat steps 1-4.

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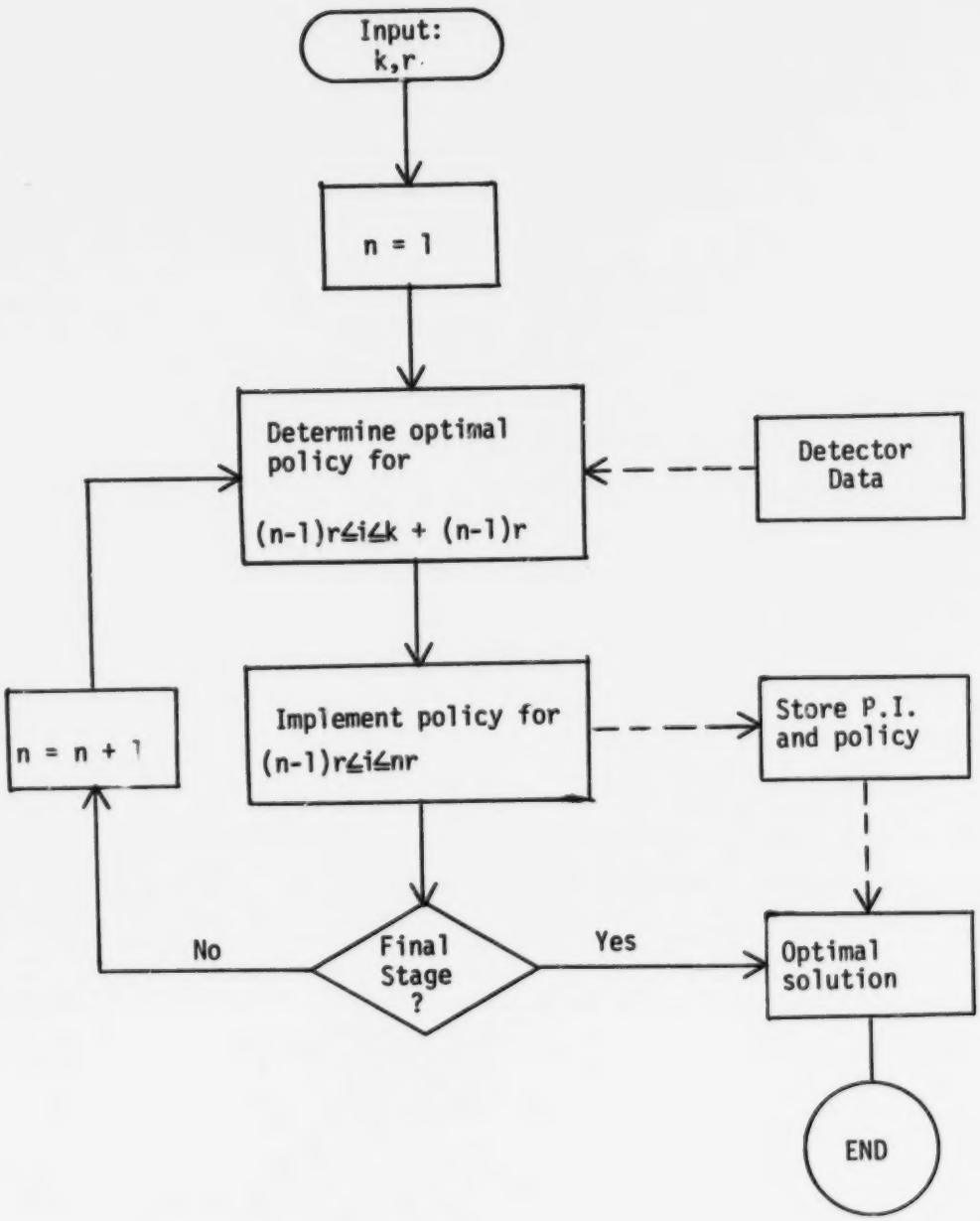

Figure 5.1: ROPAC Logic

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Implementation of this computational procedure is illustrated in detail in Figure 5.2 for the 8-min data.

5.3 Computational Results

The ROPAC strategy has been tested using actual arrivals for the head of the stage and two types of models for the tail:

1. Variable-Tail (V-T) - projected actual arrivals are taken for tail
2. Fixed-Tail (F-T) - the tail consists of a fixed flow, equal to the average flow rate during the period

The first model is only used to test the rolling horizon concept and compare the results with previous experimentations. The second model is of primary interest as it represents a practical approach to implementing ROPAC. We use measurements from upstream detectors for head data and smoothed average flows for tail data, both of which are readily available. While the tail data do not reflect accurate arrivals, their influence on the policy is minor, nevertheless important, compared with the head data and they are continuously updated in the rolling process.

Table 5.1 presents comparative results for runs done with the two types of models.

Table 5.1: ROPAC Results (k = 12, r = 3)

Type of Tail	5-min. (Q_0 = 0) Perf. Index	5-min. (Q_0 = 0) Diff. %	5-min. (Q_0 = 5) Perf. Index	5-min. (Q_0 = 5) Diff. %	8-min. (Q_0 = 0) Perf. Index	8-min. (Q_0 = 0) Diff. %
OPAC-1	196	optimum	341	optimum	148	optimum
Variable	196	0.00	356	4.40	148	0.00
Fixed	212	8.16	356	4.40	161	8.78

As one would expect, the variable-tail ROPAC produces policies that are better than those produced by OPAC-2 and, in most cases, replicate the standards produced by OPAC-1 (see Table 4.1). Fixed-tail ROPAC, although using smoothed data, comes very close to the optimal

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Figure 5.2: Rolling horizon (variable-tail) implementation in ROPAC.
(k = 12, r = 3).

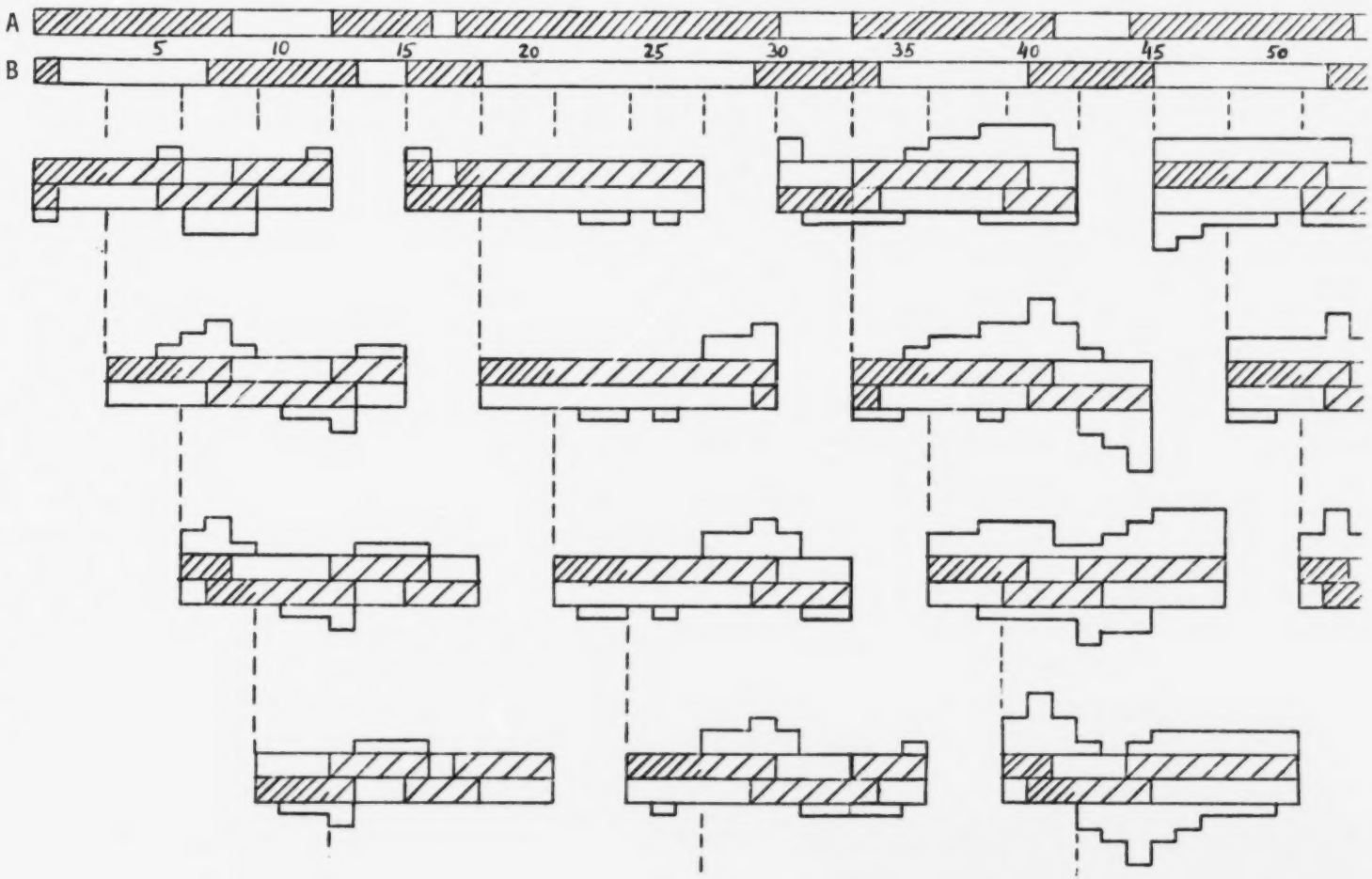

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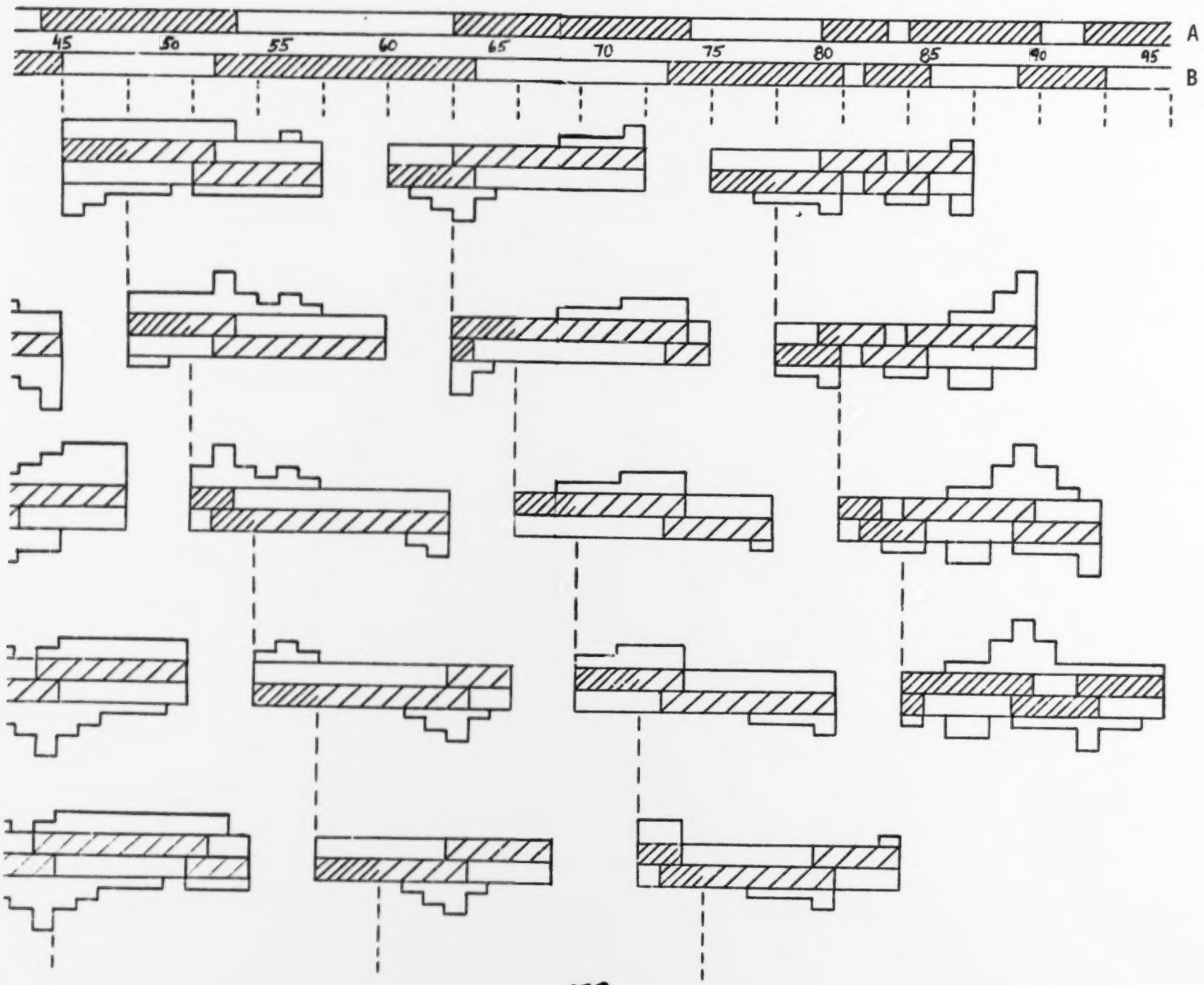
Figure 5.2 (cont'd)



and represents a feasible and very promising approach to real-time control. The policies obtained with the fixed-tail model are illustrated in Figures 5.3 and 5.4

We have also tested the sensitivity of this approach by taking actual head arrivals but assuming incorrect tail flows (in multiples of the correct values). The deviations of performance from the optimum are illustrated in Figures 5.5 and 5.6. Generally, we see that deviations are minimized when the original ratio of average flows on the approaches is maintained, i.e., the values along the diagonal of tables and sketches.

The last experiment was to test the performance of ROPAC for various levels of flow at the intersection. The program was run in a "real" mode (i.e., with real flow values rather than integer values) and all volumes were multiplied by a constant factor. Results are given in Table 5.2 and Figure 5.7. It is seen that ROPAC offers rather substantial savings compared with a fixed-time strategy such as Webster's (about 60%). These savings are impressive even when compared with strategies such as vehicle-actuated or Miller's which are only 15-25% better than Webster's [2,3,4].

5.4 Conclusions

ROPAC offers a feasible and very promising approach to real-time control. The strategy is designed to make use of readily available data, produces control policies that are almost as effective as those that would be obtained under ideal conditions, and has very reasonable computational requirements (about 2.1 CPU-sec/minute of real-time data). It appears to be well suited for implementation via microprocessor technologies.

What is, perhaps, even of greater significance is the ROPAC flow model. It considers the entire projection horizon in the optimization process and, therefore, should be amenable for application in a demand-responsive decentralized flexibly-coordinated system. In such a system one would use the analysis capabilities

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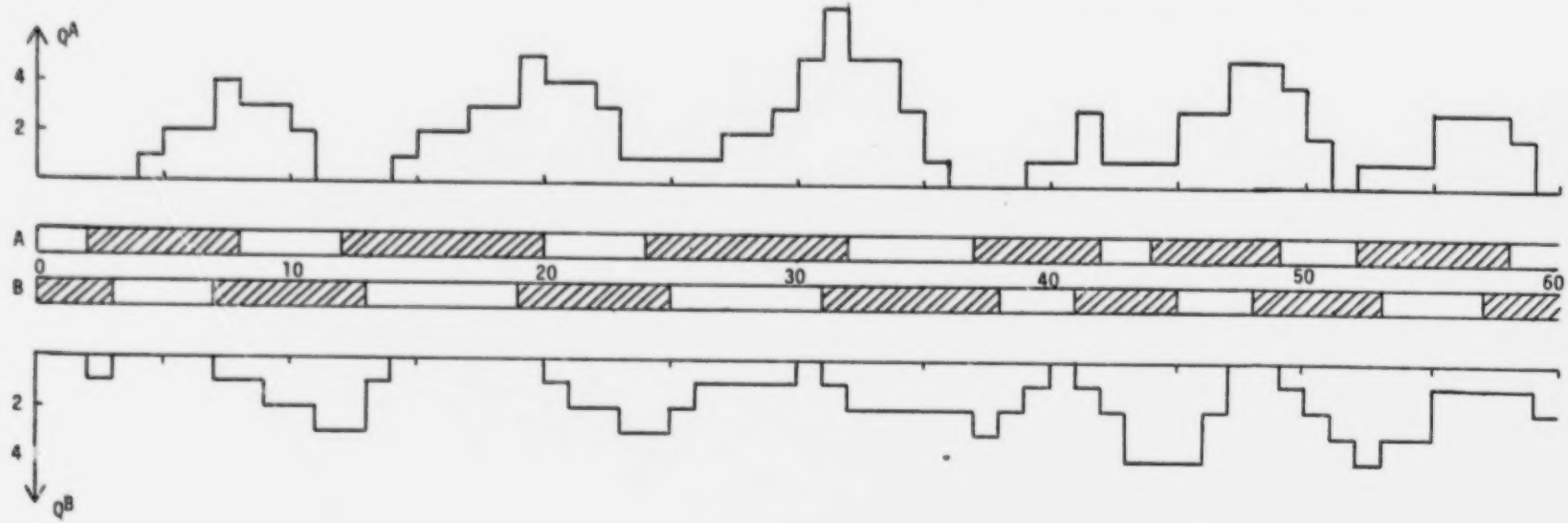
ROPAC (FIXED-TAIL): 5-minuta data, Q_0 = 0 (PI = 212)



ROPAC (FIXED-TAIL): 5-minuta data, Q_0 = 5 (PI = 356)

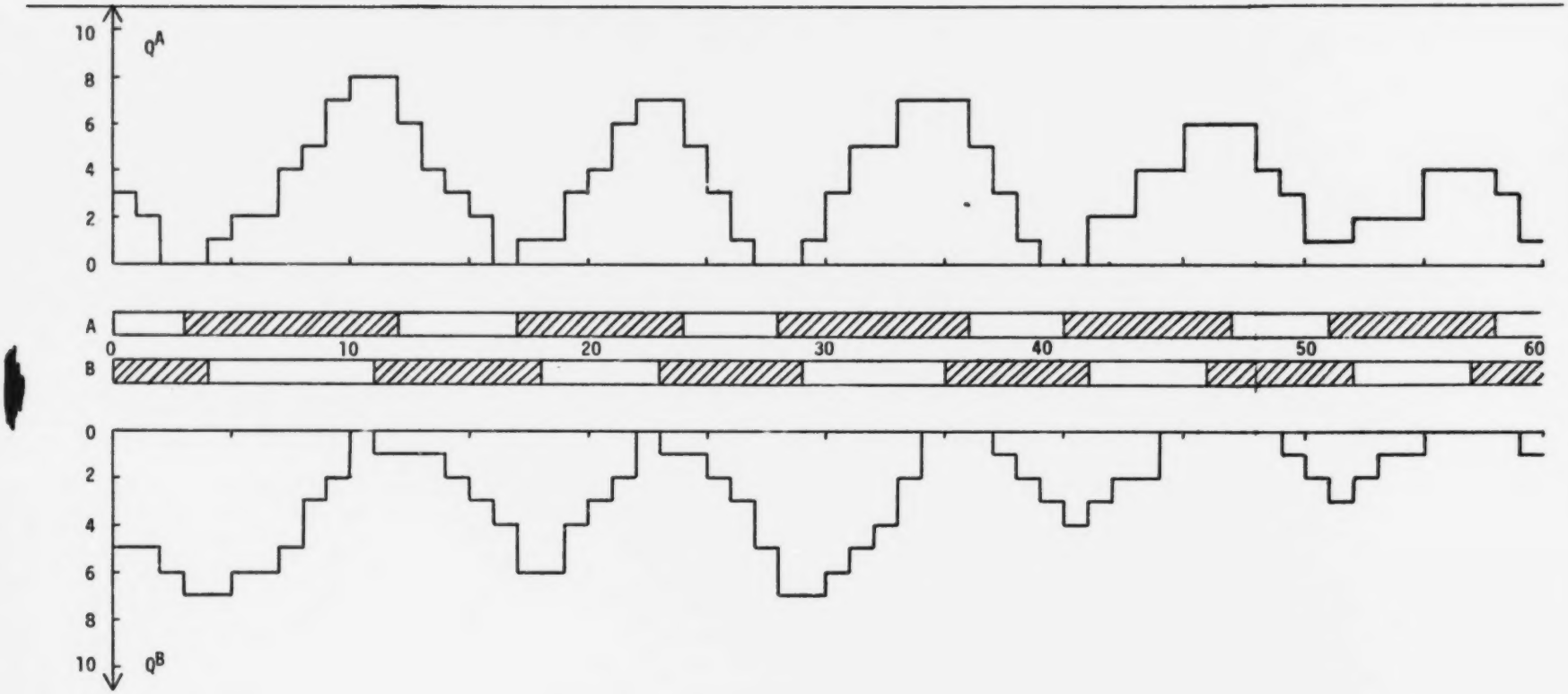


Figure 5.3B

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ROPAC (FIXED TAIL): 8-minute data (PI = 161)

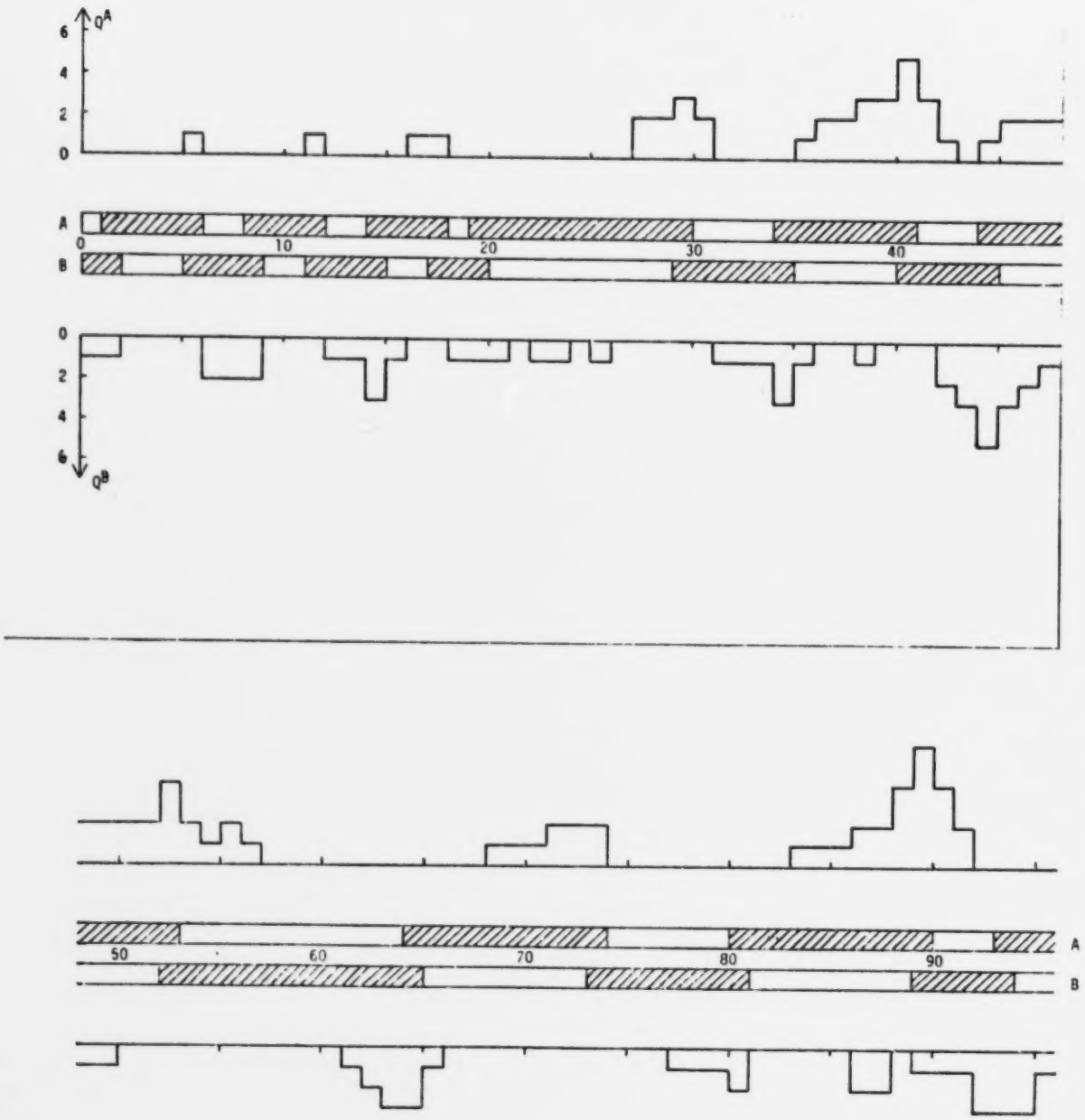

Figure 5.4

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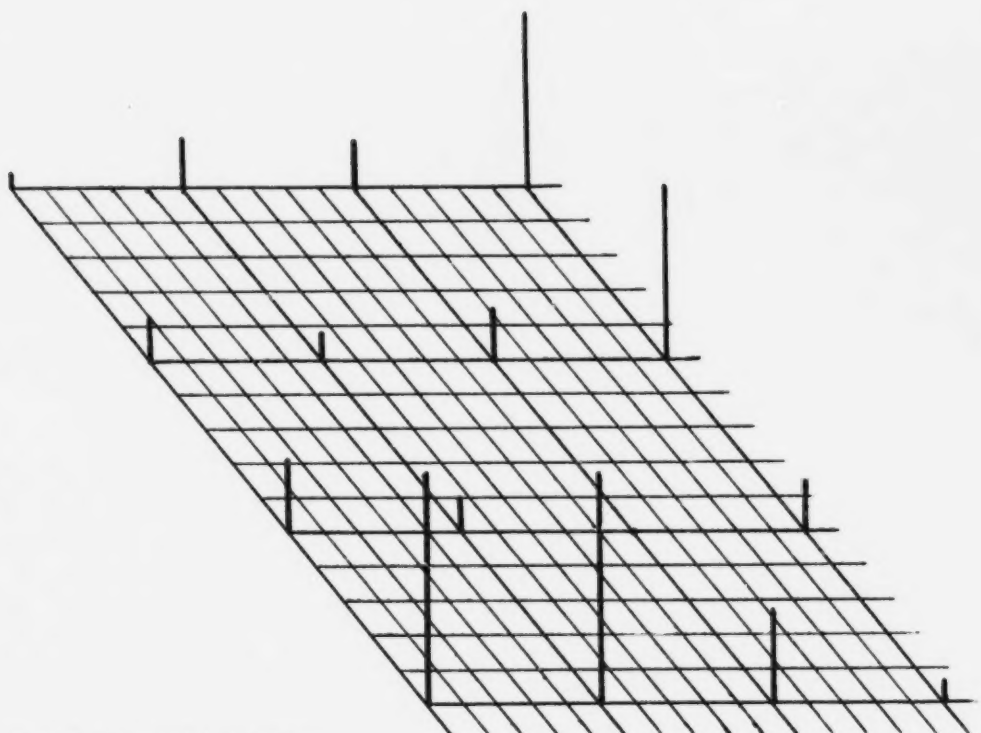
Figure 5.5: Deviation from Optimum (%)



Fixed-Tail Volume Combinations

A \ B	0	v^B	$2v^B$	$3v^B$
0	4.1	14.3	13.3	50.0
v^A	11.7	8.2	13.3	50.0
$2v^A$	21.4	9.7	0.0	13.8
$3v^A$	66.8	66.8	26.5	5.6

5-Minute Data

Optimum PI = 196

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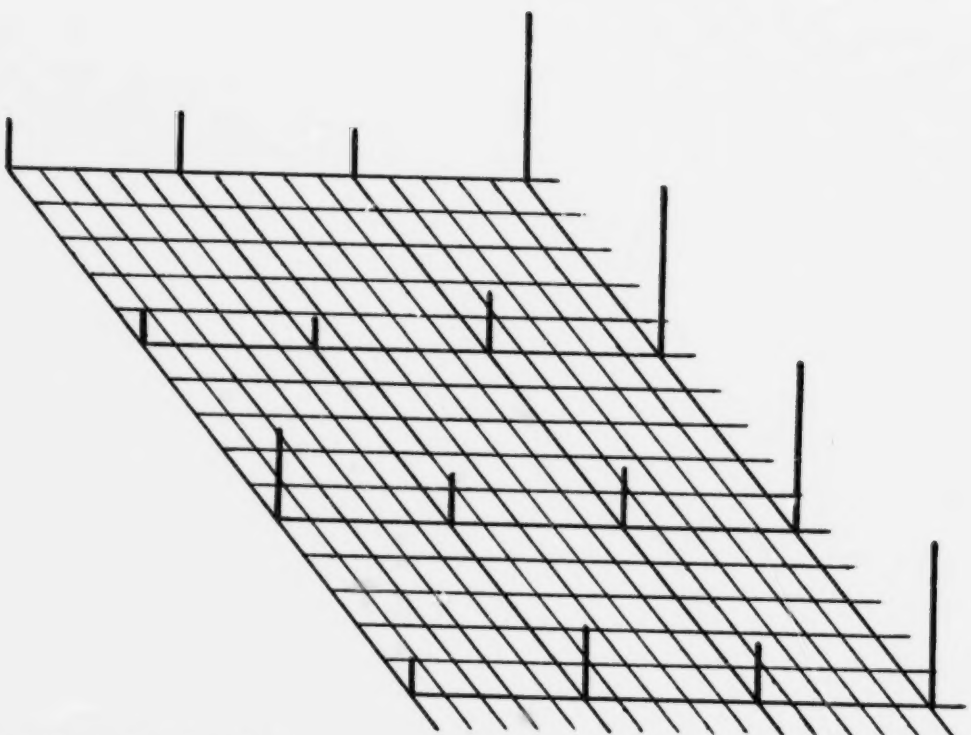
Figure 5.6: Deviation from Optimum (%)



Fixed-Tail Volume Combinations

A \ B	0	v^B	$2v^B$	$3v^B$
0	14.2	16.9	12.8	48.0
v^A	9.5	8.9	17.6	48.0
$2v^A$	25.7	14.2	17.6	48.0
$3v^A$	9.5	20.9	17.6	48.0

8-Minute Data
Optimum PI = 148

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Table 5.2: Performance Results for Various Flow Levels

STRATEGY \ Volume (vph)	500	700	855	1100	1250
WEBSTER:					
Avg. Delay (sec)	10.5	14.4	18.9	34.5	63.5
Cycle (sec)	30.6	38.9	49.2	84.7	151.6
Volume/Capacity	0.52	0.65	0.75	0.87	0.93
V-T ROPAC:					
Perf. Index	48.5	93.5	148	406.4	708.1
Avg. Delay (sec)	3.67	5.01	6.49	13.86	21.24
(Fraction of Webster)	(0.34)	(0.35)	(0.34)	(0.40)	(0.33)
Avg. Cycle (sec)	45.7	50.5	56.5	56.5	80
F-T ROPAC:					
Perf. Index	52.6	112.2	161	436.6	695.2
(Deviation from V-T)	(+8.5%)	(+20%)	(+8.8%)	(+7.4%)	(-1.8%)
Avg. Delay (sec)	3.95	6.01	7.06	14.9	20.86
(Fraction of Webster)	(0.38)	(0.42)	(0.37)	(0.43)	(0.33)
Avg. Cycle (sec)	50.5	50.5	56.5	56.5	80

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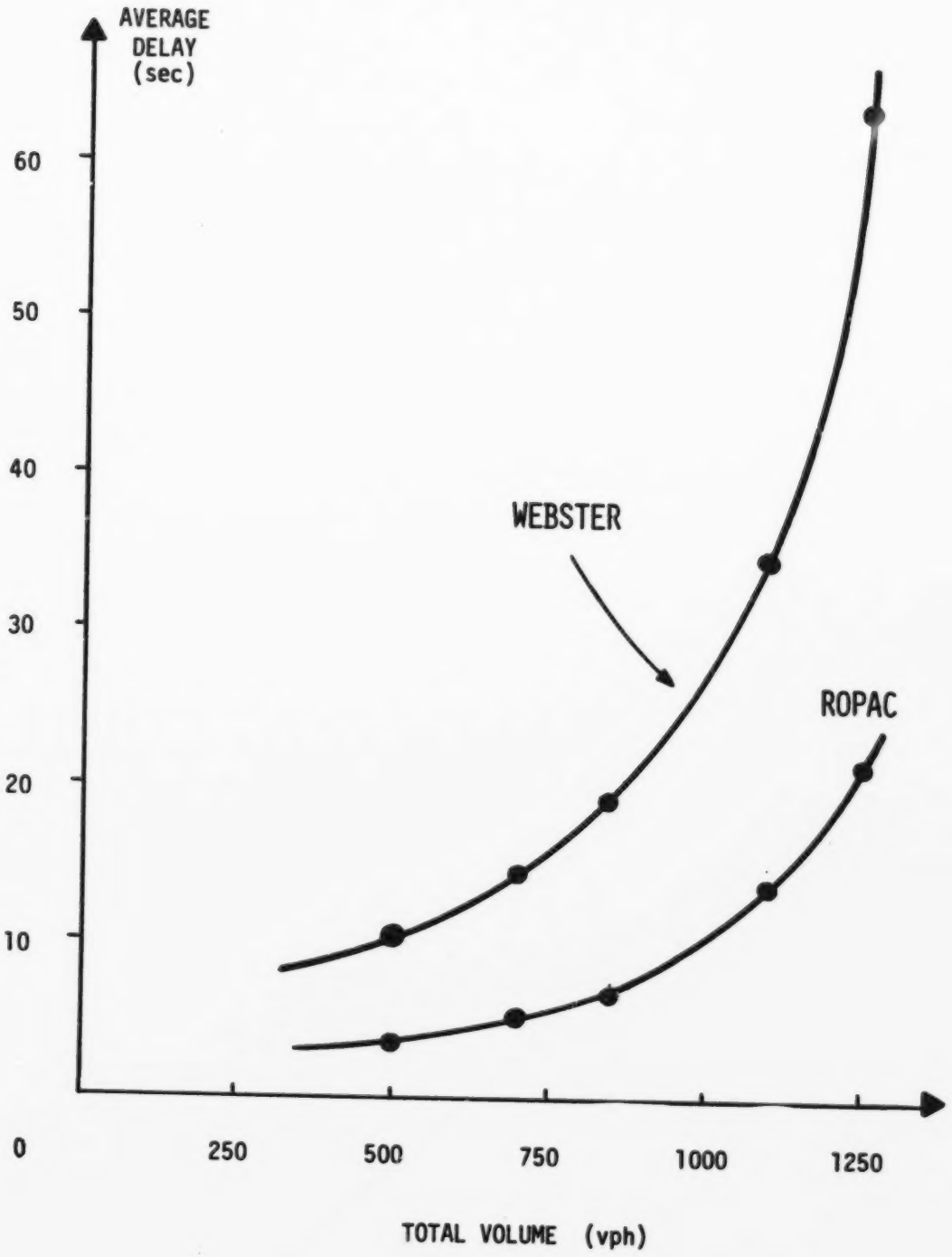

Figure 5.7: Comparison of average delay per vehicle. (Data from Table 5.2).

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of ROPAC to structure the flows in the traffic network so that coordination can be preserved on the one hand, while taking advantage of the ever present variations in flows on the other. Thus, the system would require both local analysis capabilities and communication with adjacent controllers. A sketch of the envisioned information flow is illustrated in Figure 5.8. The development of such a system is the goal of the next phase of this research.

5.4 References

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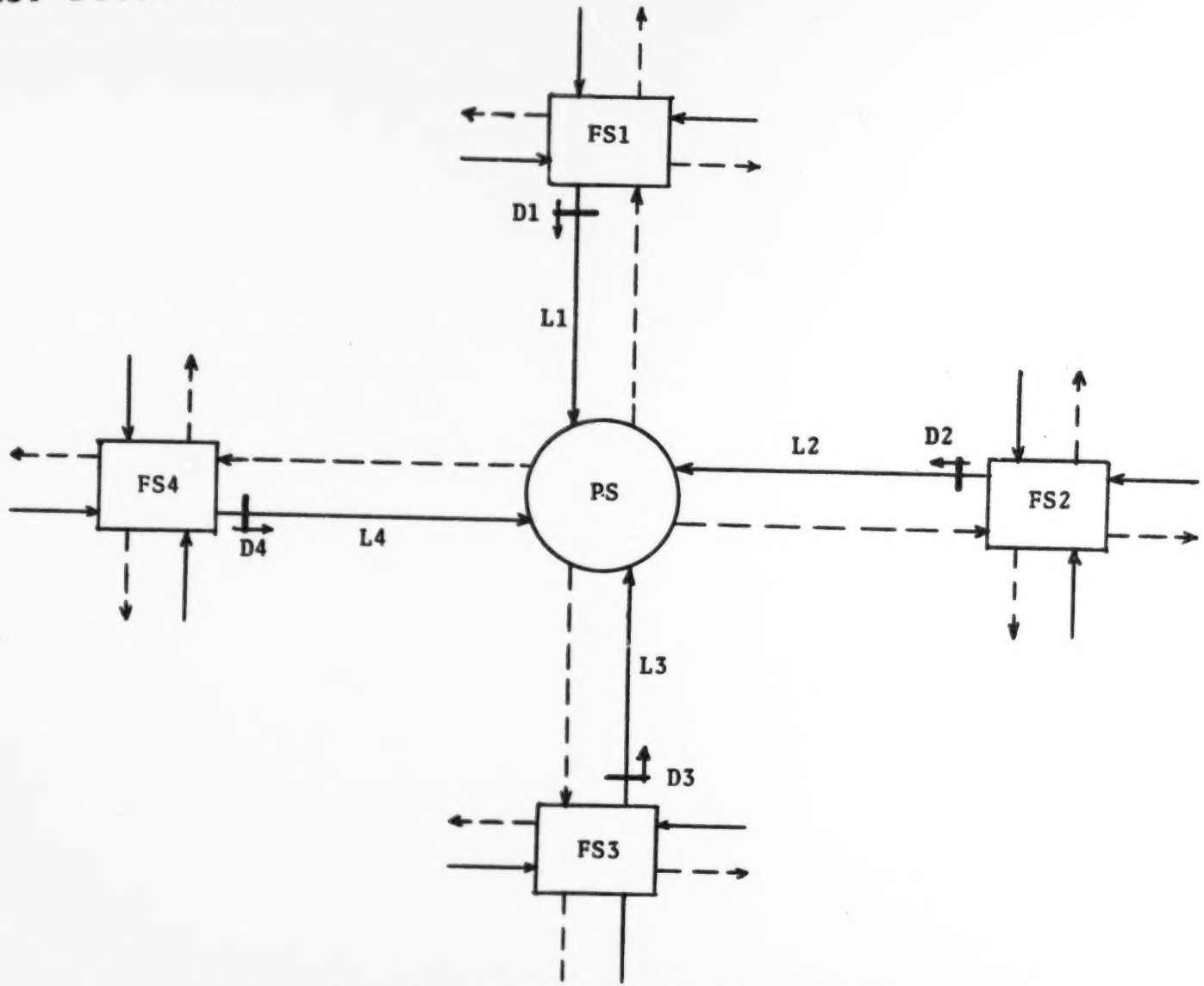

Figure 5.8: Information flow for on-line traffic model
(PS-primary signal, FS-feeder signal, D-detector, L-link)

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